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Fragmentation in Asset Markets: the price discovery implications of competitive fragmentation in equity and cryptocurrency markets.

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Fragmentation in Asset Markets:

The price discovery implications of competitive fragmentation in equity and cryptocurrency markets

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Abstract

This thesis examines fragmentation in asset markets. A taxonomical framework is developed to characterise the motivational factors behind the innovations that result in market fragmentation. Drawing on this framework and the relevant literature this thesis empirically examines the relationship between fragmentation and one of the motivational factors, reductions in information asymmetry, otherwise known as price discovery, within equity and cryptocurrency markets. Rational expectations theory is a cornerstone of the efficient market hypothesis and the basis of models proposed by Kyle (1985) and Glosten and Milgrom (1985) and their derivatives. The theory suggests that investors use available information, past experiences, and their own rational expectations to make decisions that influence asset valuation. Tests regarding whether market fragmentation contributes to the dispersal of fundamental price adjusting information are imperative in determining the role competition amongst exchanges plays in the market's ability to maintain prices at efficient levels. If prices are to remain efficient, and information asymmetry kept to a minimum, exchanges must incorporate relevant information across all trading platforms. Such a process is made more difficult and time-consuming as information becomes more decentralised or fragmented.

The term 'market fragmentation' is used heterogeneously within the literature to refer to events that segregate market participants from one another or when prices across trading platforms deviate from the fundamental equilibrium. Competitive fragmentation describes events that place investors trading a common asset into separate trading pools due to competition among exchanges. Fragmentation based on investor type differentiates between investors based on characteristics such as geographic location and investor class. Substitutionary fragmentation occurs when markets present investors with the option to purchase derivative products or assets that are considered direct substitutes for existing products. Financial fragmentation refers to periods when assets deviate from their fundamental value across a subset of exchanges.

The first study adapts and expands upon the taxonomies presented by Avlonitis, Papastathopoulou, and Gounaris (2001) and Tufano (1989). It establishes that most innovations that lead to competitive, investor based and substitutionary fragmentation, are motived by a desire to reduce transaction costs, with reductions in information asymmetry playing a supporting role. These innovations are often modifications or extensions to existing services. Modern motivational factors exert greater influence over recent fragmenting innovations and represent the formation of new products or trading methods. Technological

shocks and globalisation are most responsible for fragmenting events involving dark pools, cryptocurrencies, and high-frequency trading.

The second study investigates the role of order book transparency on the relationship between price discovery and market fragmentation. It utilises Hasbrouck's (1995) information share and Gonzalo and Granger's (1995) component share to measure price discovery across 120 stocks from six European countries (2008-2016). Panel-regression results support existing theory on price discovery in equity markets in that displayed (lit) order book prices contain substantially more information than non-displayed (dark) prices (Zhu, 2014). Dark market share coefficients, which measure competitive fragmentation between lit and dark exchanges, provide additional support that dark transactions are substantially less informed than lit transactions. Informed investors are discouraged from trading in dark pools due to high levels of non-execution risk. Fragmentation is associated with greater adverse selection risk in quoting exchanges as informed investors use their informational advantage to supply liquidity (Rindi, 2008).

Mid-quotes on lit exchanges are also more informative than lit prices (Bloomfield, O'hara, & Saar, 2005; Boulatov & George, 2013). Increases in fragmentation among quoting (lit) exchanges lead to a decrease in the informativeness of lit trades versus dark trades in both the primary and consolidated lit markets. The informativeness of exchange trades as compared to quotes deteriorates with greater competitive fragmentation across lit exchanges suggesting that lit fragmentation is associated with higher levels of adverse selection. The negative relationship between price discovery and volatility further supports this claim and is consistent with the notion that the most profitable uninformed trades are being 'skimmed' by informed liquidity providers (Bessembinder & Kaufman, 1997; Easley, Kiefer, & O'Hara, 1996).

The final study applied existing research on competitive fragmentation and price discovery to cryptocurrency markets in order to test its applicability to a new asset class. Bitcoin (BTC) transaction and order book data is collected across six exchanges for both United States Dollar (USD - $) and Euro (€) order books (2017-2019). A panel-regression model on a multivariate version of Hasbrouck's (1995) information share is employed. Results confirm previous findings that market share has a positive relationship with the informativeness of exchange prices (Madhavan, 1995). Consistent with the previous study, this is attributed to informed investors migrating to competing exchanges to better conceal and profit on their

superior information. This, in turn, increases events of information asymmetry as exchange prices become more informative and dispersed across an increasing number of exchanges.

The results contained in this thesis suggest that competitive fragmentation is in part, motivated by the intention to reduce information asymmetry. However, in practice information asymmetry increases. Competing exchanges attract a disproportionate amount of uninformed trading, though some informed investors follow the uninformed to competing exchanges in order to capitalise on their informational advantage. Finally, consistencies are found between equity and cryptocurrency markets suggesting that theories developed around traditional asset classes are transferable to the newly formed market for cryptocurrencies.

Keywords

Fragmentation, competition, price discovery, market microstructure, innovation

Declaration by Author

This thesis is submitted to Bond University in fulfilment of the requirements of the degree of Doctor of Philosophy.

This thesis represents my own original work towards this research degree and contains no material which has been previously submitted for a degree or diploma at this University or any other institution, except where due acknowledgement is made.

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Abbreviations

Abbreviation	Meaning
AEX	Euronext Amsterdam
ASX	Australian Stock Exchange
AT	Algorithmic Trading
BASp	Bid-Ask Spread
BTC	Bitcoin
CPMI	Committee on Payments and Market Infrastructure
CS	Component Share
DF	Dark Fragmentation
DMS	Dark Market Share
DV	Dark Volume
EBBO	European Best Bid and Offer
ETF	Exchange-Traded Fund
E.U.	European Union
FATF	Financial Action Task Force
HHI	Herfindahl-Hirschman Index
HFT	High-Frequency Trading
IS	Information Share
ISD	Investments Services Directive
LF	Lit Fragmentation
LSE	London Stock Exchange
MC	Market Capitalisation
MiFID	Markets in Financial Instruments Directive
MS	Market Share
NBBO	National Best Bid and Offer
NYSE	New York Stock Exchange
PBBO	Primary Best Bid and Offer
RegNMS	Regulation National Market System
RLP	Retails Liquidity Program
RPI	Retail Price Improvement
SEC	Securities Exchange Commission
SORT	Smart Order Routing Technology
TSX	Toronto Stock Exchange
U.K.	United Kingdom
U.S.	United States
USD	United States Dollar
VIF	Variance Inflation Factor
VECM	Vector Error Correction Model
Vol	Total Volume

Chapter 1: Introduction

1.1 Market Fragmentation – An Overview

Markets for goods and services exist because it is more efficient to trade via a marketplace than one-on-one transactions. Initially, individuals bartered and traded with each other, but this is time-consuming and inefficient for both parties. The adoption of fiat currency as a medium of exchange revolutionised trading allowing buying to be separated from selling through the exchange of "trade value" rather than other goods or services. This also allowed merchants to specialise and for trade centres or markets for the exchange of goods to develop, typically around transport and population centres. In addition to these logistical forces, the history of institutional arrangements have shaped market development and that informal and fragmented markets have had a persistent role in trade (Casson & Lee, 2011).

This thesis investigates various aspects of financial market fragmentation. It begins by looking at the motivational factors that lead to fragmented financial markets and investigate the impact these changes have on a market's ability to maintain accurate prices. Financial markets exist to facilitate the exchange of investable assets. The formulation of explicit rules that govern and control this process are of crucial importance to efficiently pricing traded assets. Market crashes and similar financial crises have spurred regulatory bodies into passing a number of regulations. However, in their haste to avert the recurrence of such events, governing bodies may potentially promulgate sub-optimal regulations.

If prices are to be efficient, the price formation process has to incorporate new information as quickly and accurately as possible. Prices may not immediately reflect the information arriving in a market. Trading rules can create bottlenecks; for example, if the stipulated minimum change or tick is too large, small amounts of incoming information will not immediately be incorporated. Such information must be accumulated until there is a sufficient quantity to warrant a change. The widespread availability of information is another issue that influences price formation. Differences in the distribution of information, that is, when participants are denied equal access to information, result in information asymmetry. Such flaws tend to make prices inefficient. Thus, price discovery is sensitive to the trading rules or structure of markets. Any regulations that affect any of these rules would, in turn, affect the price discovery process.

Over the past two decades, investors have evolved the way they access liquidity. Previously, traditional limit order markets allowed investors access to a single quote driven exchange in which they can view advertised prices and quantities available for the sale or purchase financial assets. In contrast, market participants today are consistently accessing liquidity across multiple markets resulting in an environment in which investors no longer cluster around a single trading venue. In addition to this, markets are further fragmenting by allowing investors access to both traditional and un-advertised liquidity, herein referred to as 'lit' and 'dark', respectively. Dark liquidity differs from lit liquidity as it offers no pre-trade transparency. This study investigates the impact that fragmentation within and across lit and dark markets has on the price discovery process. Most notably, does market fragmentation cause valuable information regarding the fundamental value of an asset to leave the primary exchange and impair investors' ability to formulate accurate prices?

Technological advancements such as the creation of Smart Order Routing Technology (SORT) allow investors simultaneous access to multiple trading pools. SORT improves the probability of trade execution by finding multiple smaller counterparties to a trade across several exchanges as opposed to waiting on a perfectly complementary trade in a single location. This results in markets favouring smaller trade sizes as opposed to large block trades. It also ensures trades are executed in a timely fashion by circumventing the need for markets to remain concentrated around a single trading venue.

The Markets in Financial Instruments Directive (MiFID) is a European market regulatory policy that was first implemented on November 1, 2007. As a replacement for the Investments Services Directive (ISD) of 1993, MiFID established a single regulatory framework for the European Economic Area. The goal of this framework is to create a unified set of policies to which all competing trading venues, both lit and dark, are subject to in order to promote cross-border competition for liquidity. The three major directives that MiFID established to achieve this goal are i) the abolishment of the default and concentration rules which force trades that meet certain criteria to execute on the primary exchange; ii) increases in mandatory pre- and post-trade transparency requirements; iii) the introduction of the best-execution rule, requiring crossed trades, such as those originating from dark liquidity providers, to be executed at the midpoint of bid-ask spread.

It is the policies mentioned above that have fostered competition across not only lit exchanges but dark exchanges as well, most notably dark pools. Unlike traditional exchanges, dark pools are trading venues that offer no pre-trade transparency in that they do not advertise bid and ask quotes and their corresponding quantities to potential market participants. This exemption from pre-trade transparency rules implies that at any given time throughout the trading day the status of the order book is unknown. When two complementary trades enter the dark order book, the transaction is executed and reported. Trade execution occurs at a pre-determined time set by the operator at a price determined externally by either the primary exchange or the consolidated market order book, herein referred to as the National Best Bid and Offer (NBBO) and European Best Bid and Offer (EBBO), respectively.

L. E. Harris (1993), Hendershott and Mendelson (2000) and Gresse (2006) find that markets fragment to serve the different types of trading requirements of different classes of investors. They confirm that the ability to serve different classes of clientele is a clear benefit of fragmentation. There are, however, two conflicting views on market structure and competition regarding the extent to which fragmentation is necessary and should be controlled. The first fundamental theorem of welfare economics (Loury, 1979) talks of Adam Smith's Invisible Hand, whereby a monopoly should be restrained in favour of promoting a competitive market structure.. On the other hand, Schumpeter (2010) states that momentary monopoly power is functional and naturally eroded over time through entry, imitation and innovation. Exchanges should be allowed to compete without the need for specific rules to protect competition. An anti-trust policy that promotes static competition is not necessarily superior to a laissez-faire attitude. The optimal market structure involves a finite number of firms and endless competition is not necessarily beneficial. In markets, access to liquidity is key. If liquidity is not sufficient, alternatives must be found to improve access through better prices, self-regulation or sharing of access to order book with other firms. Otherwise, clients will be exposed to non-execution risk and will leave the exchange due to not being able to transact.

Globally, regulators have been unsure regarding what actions, if any, to take in order to stem the levels of fragmentation in equity markets resulting from recent policy changes and technological advancements. The cost of competition amongst equity providers, particularly those offering dark liquidity, has yet to be fully explored. MiFID II recently proposed limiting dark trading to 8% for any particular stock (4% in a single dark pool).

1.2 Research Problem

Regulations, such as MiFID, play a role in shaping market microstructure. However, they may not be the only factors that influence market fragmentation. It is important to identify the other factors that cause markets to fragment in order to then study their impact on market conditions such as price discovery. Therefore, the first question investigated in this thesis is:

RQ1: What are the motivating factors that lead to the fragmentation of financial markets?

To answer this question the first study adapts the models of Avlonitis et al. (2001) and Tufano (1989). It develops a unifying framework whereby various forms of fragmentation in financial markets are classified according to their degree of innovation and the motivations behind such events, respectively. Key papers relevant to the discussion are identified for each fragmentation event. The findings of the key papers, both theoretical and empirical, are summarised and interpreted regarding the impact of such events on their respective financial markets.

Existing literature on price discovery resulting from dark liquidity transactions is limited. Along with studies measuring fragmentation across multiple exchanges. However, price discovery and the reduction of information asymmetry amongst investors is important to maintaining an efficient market where investors feel comfortable trading. The first study shows that fragmentation in equity markets is in part, motivated by the desire to reduce asymmetric information. Therefore, the second research question investigated in this thesis is:

RQ2: How does competitive market fragmentation affect the equity market's ability to efficiently price assets and convey price disseminating information to the public?

This study differentiates itself from previous works by taking a more detailed look at the structure of both lit markets. It also takes into consideration the structure of the dark liquidity market itself rather than simply its market share. This study investigates the effects that competition for liquidity across dark liquidity exchange has on the price discovery process in the traditional visible exchange. In addition to observing the effects in the primary sovereign exchange, it also investigates the effects in the consolidated order book when all exchanges transacting in a particular equity stock are accounted for and treated as a single market.

The final study investigates the applicability of established microstructure theory in equity markets to cryptocurrency markets. Existing research on this topic is limited due to how new cryptocurrency markets are. However, both markets operate pre-trade transparent (lit) order books and facilitate transactions in a similar way. Much like events of competitive fragmentation in equity markets, fragmentation in cryptocurrency is also partly motivated by the desire to reduce levels of information asymmetry. Therefore, using established research in equity markets, this third study aims to answer the question:

RQ3: How does competitive market fragmentation affect the cryptocurrency market's ability to efficiently price assets and convey price disseminating information to the public?

1.3 Research Contribution

This thesis contributes to existing research in several ways. The first study expands upon existing reviews of fragmentation in financial markets such as Gomber, Sagade, Theissen, Weber, and Westheide (2017). Gomber et al. (2017) focus primarily on pre-trade transparent (lit) equity markets, and to a lesser extent non-pre-trade transparent (dark) equity markets as well. They identify and discuss the events that lead towards the formation of new equity exchanges. This thesis expands upon their ideas by covering fragmentation events across not only equity markets, but also cryptocurrency and debt. Focussing on more asset classes allows for an increase in scope when identifying and classifying the different ways in which the term fragmentation is applied to financial markets. Focussing on a wider range of definitions also allows for more detailed comparisons across markets. It also allows for greater identification of the similarities behind motivating factors leading to fragmentation, the degree of innovation introduced, and their resulting impacts.

This thesis, particularly the second and third studies, contribute to the regulatory discussion by investigating various forms of fragmentation in equity and cryptocurrency markets across Europe and how they impact the market's ability to adjust prices to new information in a timely manner. European markets are no longer limited by their location and can participate in cross-border trading. The pan-European market is considered to be a virtual market with multiple entry points (O'Hara & Ye, 2011). By using data from six European countries over a long study period (November 1 2008 to October 31 2016) a more complete picture of the affects fragmentation has on price discovery is formed, compared to other studies. This is crucial as policies such as MiFID, and more recently, MiFID II, are applied across all members of the European Union (E.U.). Analysing equity data from a single geographical location does not provide insight regarding which policies regulators should focus on in order to provide the greatest protection to E.U. investors. In line with previous studies (Degryse, De Jong, & Kervel, 2015; Gresse, 2017), the second study analyses results from both the primary exchange and the global (pan-European) consolidated market. Primary and global parameters are used in order to distinguish between the effect faced by local investors, who predominately access the national exchange in their country and institutional investors who can access multiple exchanges simultaneously. This aids in distinguishing how fragmentation impacts both retail investors who largely access the dominant exchange in the market and the consolidated market as a whole where more sophisticated institutional investors can access liquidity from multiple markets simultaneously.

Dark pools have come under scrutiny with regards to the role they place in the price discovery process. In May 2009, James Brogagliano of the Securities and Exchange Commission (SEC) stated that dark pools could impair the price discovery process by drawing valuable order flow away from the public quoting market. He also added that anything that significantly detracts from the incentive to display liquidity in the public market could decrease the available liquidity in the market. This would, in turn, harm price discovery and lead to increased short-term volatility.[1]

By using the lit market order book prices as a crossing point, researchers argue that the dark market does not contribute directly to price discovery. The goal of the traditional dark pool customer is to execute a large order without affecting the market price during the sale. They are intended to be passive investment funds that are interested in adjusting their position. However, recently we are observing the prevalence of small transactions that likely originate from algorithmic trading systems such as SORT (Nimalendran & Ray, 2014) and contain some amount of price adjusting information. Many dark pools allow for prices to deviate from the midpoint through the use of limit orders. Alternatives to mid-point prices allow investors to gain a more favourable price or improve the speed of the transaction by sacrificing a portion of their price advantage. As a result, dark trades do emit some amount of information (Kaniel & Liu, 2006).

The second study contributes to the price discovery research with a focus on dark liquidity in several ways. It begins by continuing to explore the effects resulting from inter-market fragmentation of lit and dark orders. However, it extends this literature to empirically study the effects of intra-market fragmentation within the dark market in a similar fashion to which existing studies focus on intra-market fragmentation within lit exchanges.

[1] See 'SEC's Brogagliano on the need for Market Structure' (http://mutualfunddirectorsforum.blogspot.com.au/2009/05/secs-brigagliano-on-need-for-market.html).

The second study is also only the second study to measure fragmentation in the dark pool market utilising the same constructs previous studies have applied to lit exchanges. It is, however, the first to apply this construct to study price discovery. This thesis complements the empirical work of Comerton-Forde and Putniņš (2015) who use Australian Securities Exchange (ASX) data to conclude that dark trading harms markets by increasing adverse selection risk on lit exchanges. They also find that high levels of dark trading can impede informational efficiency. Other papers focus on the liquidity implications of dark trading and lit market fragmentation. Buti, Rindi, and Werner (2011) analyse United States (U.S.) data on 11 dark pools and find that liquid stocks tend to be more attracted to dark pools. Stocks tend to favour dark pools on days with high volume, high depth, low volatility, and low absolute returns. Increased dark pool use also has a positive impact on market quality measures such as spreads, depth, and volatility. Nimalendran and Ray (2014) use data on 32 U.S. dark pools and find that algorithmic trades for illiquid stocks are associated with higher spreads and price impact. Dark trades are found to contain less information than lit trades and algorithmic trading is used to spread activity across both lit and dark exchanges. Degryse et al. (2015) use data on Euronext Amsterdam (AEX) mid and large-cap stocks over a two-year period from November 1 2007 to November 1 2009. Their timeframe aligns with the introduction of MiFID policies. They find that lit fragmentation improves liquidity across the global order book, though it does so at the detriment of local liquidity on the primary exchange. Dark trading, however, is largely detrimental to liquidity. Gresse (2017) studies data on eight stock exchanges in conjunction with a trade reporting facility for the London Stock Exchange (LSE) and Euronext listed equities. They find that lit fragmentation is detrimental to the depth of smaller stocks while neither dark trading nor lit fragmentation is found to harm liquidity.

Finally, the third study is the first to measure the level of fragmentation in the cryptocurrency market and study its relationship to the price discovery process. It is also the first study to apply established research surrounding rational expectations theory and the efficient market hypothesis to cryptocurrency markets. Therefore, the third study is the first to apply these techniques, largely used for equity markets, and test the extent to which they, and existing theory on competition, applies to the cryptocurrency market.

1.4 Structure of the Thesis

The thesis addresses the question surrounding the factors which lead to the fragmentation of financial marks and how these events affect a market's ability to convey price disseminating information to the public. The thesis is structured in three chapters, each which represent a distinct body of material related to the underlying research question. The following chapter, Chapter 2, develops a framework based on the prior literature through which is used to investigate various forms of fragmentation and how they relate to financial innovation. Chapter 2 draws upon the taxonomies of Avlonitis et al. (2001) and Tufano (1989) and extends these works to consider various financial innovations that cause markets to fragment. The framework is used to identify and categorise the various forms of fragmentation discussed in the literature. Chapter 2 identified four fragmentation classes: competitive market fragmentation, fragmentation based on customer type, substitutionary fragmentation, and financial fragmentation. The literature reviewed reveals instances of innovation in all fragmentation classes, with the exception of financial fragmentation, to be internally motivated and result in permanent changes to financial markets. Financial fragmentation is temporally determined and relates to periods when markets are in disequilibrium, which naturally correct over time.

Chapter 2 then drills down into subclasses within each fragmentation class and finds that most innovations leading to fragmentations are motived by a desire to reduce transaction costs. A reduction in information asymmetry plays a supporting role in many instances of fragmentation. We observe that the modern motivational factors, such as technological shocks and globalisation, exert greater influence over more recent fragmenting innovations, especially for fragmentations relating to dark pools, cryptocurrencies, and high-frequency trading. Another dimension to the framework is the degree of innovation associated with various types of fragmentation which vary among fragmentation types. Competitive market fragmentation events involve modification of existing services while fragmentation based on customer types involve the extension of services. Finally, substitutionary fragmentation results in new innovations that differ widely from existing financial products.

The framework developed in Chapter 2 forms the background for two empirical studies detailed in Chapters 3 and 4. Chapter 3 explores fragmentation in equity markets, examining the price formation process in lit and dark markets. Chapter 4 investigates the price formation process in the fragmented cryptocurrency market. Each of these empirical chapters are discussed below.

Chapter 3 reports on an empirical study which tests existing theory on price discovery in equity markets. The study finds that lit prices contain substantially more information than dark prices and that mid-quotes on lit exchanges are more informative than lit prices. The study tests and supports the hypothesis that increases in fragmentation among quoting (lit) exchanges lead to a decrease in the informativeness of primary market lit trades versus dark trades. However, it rejects the hypothesis that global consolidated market trades become more informative as lit markets fragment. The finding that dark transactions are substantially less informed than lit transactions is further supported by the dark market share coefficients. These measure the inter-market fragmentation between lit and dark exchanges. The study shows that informed investors are discouraged from relying on dark pools as they tend to experience greater non-execution risk as they cluster on the heavy side of the market. The study shows that fragmentation is associated with greater adverse selection risk in quoting exchanges as informed investors use their informational advantage to supply liquidity (Rindi, 2008). The results show that the effects are greater in local exchanges as global market benefit from a more diverse subset of investors. Dark market fragmentation is therefore associated with a concentration of informed order flow in quoting exchanges.

The empirical study in Chapter 3 shows that greater intra-market lit fragmentation increases the informativeness of exchanges trades as compared to quotes deteriorates. This suggests that intra-market lit fragmentation is related to increased adverse selection in the lit market. A negative relationship between price discovery and volatility is observed which further supports this finding. Overall, these results are consistent with the notion that informed liquidity providers 'skim' the most profitable uninformed trades (Bessembinder & Kaufman, 1997; Easley et al., 1996).

Chapter 4 reports the results of the third study. This study empirically examines fragmentation in the cryptocurrency markets and the impact on price discovery. The results suggest that increased market fragmentation either leads to an increased concentration of informed investors on the dominant cryptocurrency exchange or the introduction of informed investors on smaller satellite cryptocurrency exchanges. The implication is that investors can no longer look towards a single exchange to gather all relevant price adjusting information. The process of price discovery, that is, the process of forming an accurate opinion of prices levels, becomes more difficult. The more the market becomes fragmented the more investors protect themselves against the risk of information asymmetry and adverse selection by widening bid-ask spreads. This leads to a reduction of market quality factors such as bid-ask spreads. The widening of bid-ask spreads is seen as a negative outcome to cryptocurrency market fragmentation as it increased the cost of a round-trip transaction for investors.

The lower Frag coefficients for less liquid exchanges also explains supports the notion that these exchanges find it more difficult to locate a counterparty for the informed traders when compared to more liquid exchanges (Mendelson, 1987). So, when markets fragment, and smaller exchanges entice some investors to transact in their order books, the increases in fragmentation they cause is able to support some trading activity. But once again, these smaller exchanges largely attract uninformed traders.

Finally, Chapter 5 summarises the results and relates the findings to the key research questions. Chapter 5 discusses the implications of the thesis for theory, policy, practice, and education. It also highlights the limitations of the study and proposes ideas for future research in market microstructure.

In summary, the thesis builds a framework of the factors motivating the development of innovations that lead to market fragmentation. (Chapter 2). The thesis then empirically examines the price discovery implications resulting from fragmentation in equity and cryptocurrency markets. Using the taxonomy developed in Chapter 2, Chapter 3 studies the relationship between fragmentation levels and one of the motivating factors, reductions in information asymmetry (price discovery). Chapter 4 extends this research to the fragmented cryptocurrency market. Once again, price discovery is made more difficult and bid-ask spreads widen to compensate. The overarching implication for price discovery is that fragmented markets make it more difficult to consolidate all relevant pricing information and impede price discovery. Finally, Chapter 5 summarises the results and discusses their implications.

Chapter 2: Financial Innovation and Market Fragmentation

2.1 Introduction

Market fragmentation is motivated by innovations in products and services. This chapter focuses on the role that innovation plays in fragmenting financial markets. A key paper by Miller (1986) on the financial innovations of the 1960s to the 1980s shows a significant incidence of financial innovations in that 20-year period and argues that the trend in financial innovation is unlikely to subside. History supports this prediction as financial markets have introduced numerous new products, processes and market types. Products such as cryptocurrencies and exchange-traded funds and processes such as dark pools, retail investor programs, and high-frequency trading are the tip of the iceberg and represent only a subset of the more successful programs. Innovation is a continuous process anchored by the market's willingness to experiment in its efforts to provide participants with new or modified services aimed at filling a void in the existing market's offerings.

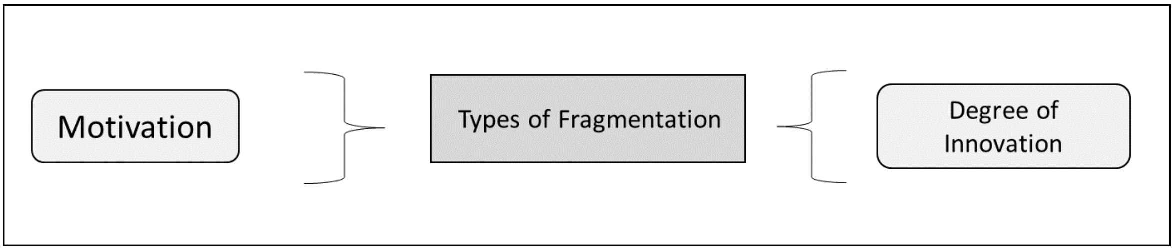

Figure 2-1: Taxonomy of Market Fragmentation (Overview)

This chapter adopts the models of Avlonitis et al. (2001) and Tufano (1989) and develops a unifying framework of market fragmentation. Various forms of fragmentation in financial markets are classified according to their degree of innovation and the motivations behind such events (see Figure 2-1). To develop the framework, key papers pertaining to each fragmentation event are identified and discussed. This chapter discusses how the existing literature, both theoretical and empirical, interpret the impact of such events on their respective financial markets. Finally, the chapter identifies two current type of competitive market fragmentation for further empirical study that form the focus of the remainder of the thesis.

This chapter expands upon existing reviews of fragmentation in financial markets such as Gomber et al. (2017) in several ways. Gomber et al. (2017) focus primarily on pre-trade transparent (lit) equity markets, and, to a lesser extent, non-pre-trade transparent (dark) equity markets. They identify and discuss the events that lead to the formation of new equity exchanges. This chapter expands upon the work of Gomber et al. (2017) by covering fragmentation events across cryptocurrency and debt markets in addition to equity markets. A wider range of asset classes allows for an increase in scope when identifying and classifying the different ways in which studies apply the term 'fragmentation' to financial markets. This, in turn, allows for greater comparison across markets and identify similarities behind their motivations, the degree of innovation, and their resulting impacts.

In addition to exchange-based fragmentation events, this chapter identifies fragmenting events in financial products. Product-based fragmentation events are defined by the introduction of new product classes or direct substitutes to existing offerings. Concentrating on products, in addition to services, allows for a more comprehensive review of how innovation leads to fragmentation across financial markets as a whole. Excluding product-based fragmentation would limit the scope to exchanges and other tools offering investors a medium for the exchange of financial assets. The goal is to show that innovation is a leading factor behind the numerous occurrences of fragmentation across financial markets.

Innovation is widely used to describe both shocks to financial markets and how markets react to such shocks. In general terms, financial innovation is synonymous with the creation of new financial products as well as the tools used by market participants to transact in those products. Avlonitis et al. (2001) and Tufano (1989) classify forms of innovation into either 'product' or 'process'. Product innovations involve the creation of new types of financial instruments based on existing offerings. Derivatives such as options and futures are a common example of product innovations. Product innovation also includes the formation of new financial instruments outside the scope of existing offerings such as cryptocurrencies.[2] Process innovations pertain to the creation or modification of new methods by which financial securities can be distributed and accessed by investors. Some examples of these include the formation of new exchanges and the introduction of new investor classes.

Figure 2-2 presents a general taxonomy of market fragmentation and classifies the general forms of market fragmentation investigated in this study under both the 'product' and 'process' innovation categories. The general forms of market fragmentation include competitive market fragmentation, fragmentation based on customer types, and substitutionary fragmentation. Competitive market fragmentation is classified as a process-based event as it pertains to fragmentation across exchanges that provide access to financial products. These exchanges include lit equity exchanges, dark equity exchanges, other-off

[2]See Section 2.4 for an in-depth discussion on both forms of product innovation.

exchange providers, and cryptocurrency exchanges. Fragmentation based on customer types is also a process-based event as it identifies changes to how investors access liquidity within a particular exchange. Fragmentation events based on customer type include the separation of retail and institutional orders, as well as the inclusion of foreign investors and high-frequency traders. Substitutionary fragmentation is predominantly a product-based event as it involves the creation of new investment products which often compete with exist investor offerings. We identify equity substitutes, such as derivative products, and the creation of competing (alternative) cryptocurrencies as the main forms of Substitutionary fragmentation currently discussed within the literature.

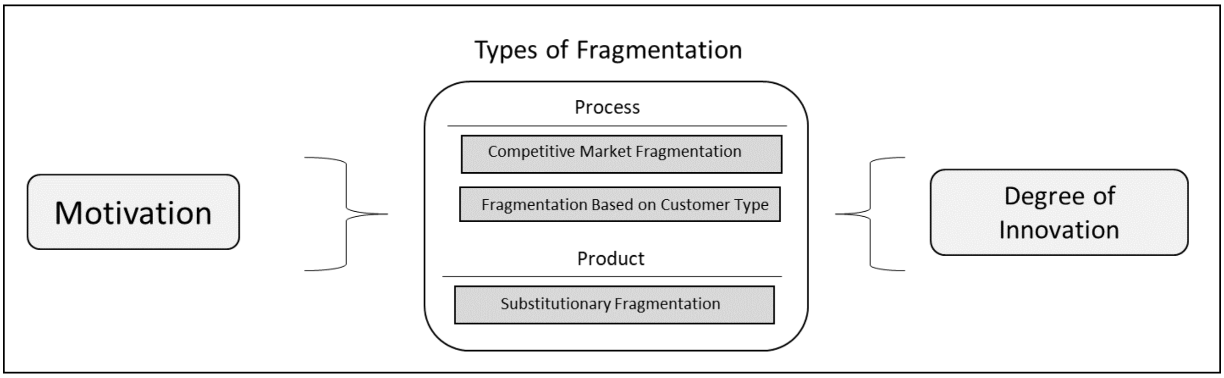

Figure 2-2: Taxonomy of Market Fragmentation (Product and Process)

The final form of fragmentation discussed in this chapter, financial fragmentation, exists outside of the process and product innovation classification of Avlonitis et al. (2001) and Tufano (1989). Unlike the three previous forms of fragmentation, financial fragmentation is a result of external market shocks and represents the consequence resulting from changes in market conditions. The previous forms of fragmentation are considered internally driven whereby they would not exist were it not for the explicit actions of market participants. Internally driven fragmentation factors represent the conscious actions of participants aiming to permanently change the structure of the market, while externally driven fragmentation factors are often a temporary symptom of market conditions. Therefore, we propose 'pricing' as a third classification innovation and financial fragmentation. The result is what we refer to as the three Ps of fragmentation, as depicted in Figure 2-3: process, product, and pricing.

Tufano (1989) argues that markets innovate to correct for imperfections in existing offerings. These imperfections include, but are not limited to, taxes, transaction costs, and informational asymmetries. Tufano (1989) states that the presence of these imperfections encourages participants to seek alternatives to fill gaps in the existing financial offerings. Doing so makes markets more complete and brings us closer to a state in which further innovations no longer benefits individual participants, nor the market as a whole. Miller (1986) suggests that subsequent attempts at innovation lead to neutral mutations. While providing an alternative to existing offerings, neutral mutations do not provide additional benefits. Instead, they provide alternative methods to achieve a state that is complementary to the existing one.

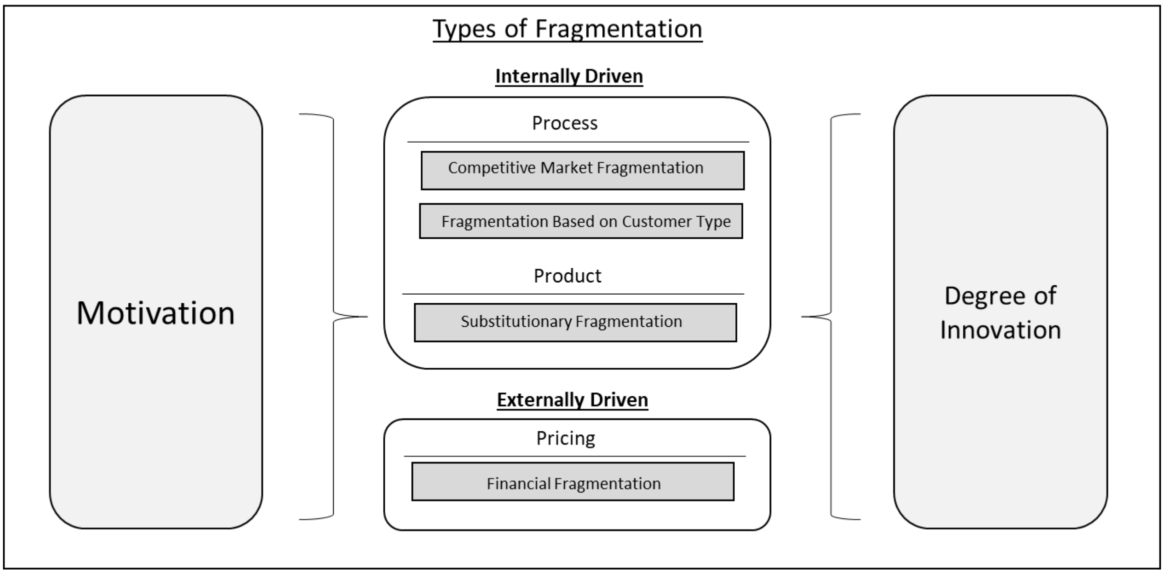

Figure 2-3: Taxonomy of Market Fragmentation (Three Ps)

Tufano (1989) uses a combination of existing financial innovations classifications and historical events and presents six key motivational factors behind various events of financial innovation. This study uses these six factors to evaluate the motivation behind recent market fragmentation events. These six factors, depicted in Figure 2-4, are as follows: i) minimise transaction, search and market costs; ii) address agency concerns and information asymmetry; iii) complete incomplete markets; iv) response to taxes and regulation; v) globalisation and risk management; vi) technological shocks. Historically, the first four factors are the predominate forces motivating innovation that leads to market fragmentation. However, globalisation and technological shocks play a greater role in more modern instances of fragmentation, particularly in the dark equity and cryptocurrency categories, the foci of this thesis. In addition to the six factors proposed by Tufano (1989), a seventh factor, economic shocks, is proposed as a contributor to reactionary and externally driven fragmentation events, most notably financial fragmentation.

Finally, the model presented by Avlonitis et al. (2001) is adapted to reflect the degree of innovation within the market as a whole. Originally, Avlonitis et al. (2001) classify the degree of innovation at a firm level. Therefore, their taxonomy differentiates between firm-level and market-level innovations. As an example, the model distinguishes between innovations that are new to the firm itself or represent a new offering that is unlike anything currently available across the market as a whole. For simplicity, the proposed taxonomy only considers market-wide innovations resulting from fragmenting events. The three degrees of innovation considered in this study are modifications, extensions, and new innovations. Figure 2-4 presents the degrees of innovation in ascending order of their contribution to innovation. Modifying existing offers is the least innovative as it can be as simple as modifying a single parameter of a product or process. Extensions to product lines are considered to be more innovative as they require the addition of new features into existing product or service offerings. Finally, the creation of new products or services is considered the most innovative as it is the most labour intensive and the least likely to resemble anything currently available to market participants.

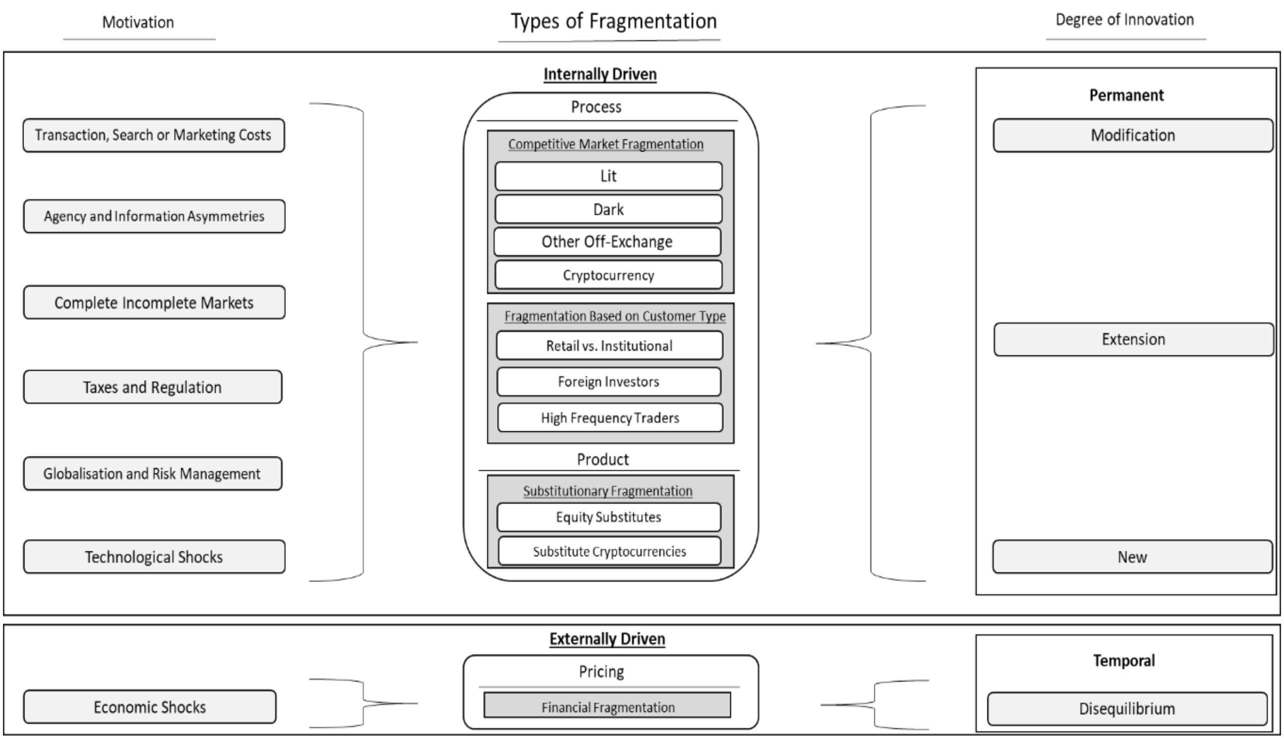

Figure 2-4: Taxonomy of Market Fragmentation (Framework)

The classifications represented by Avlonitis et al. (2001) have a commonality in that they correspond to a permanent change in market conditions. However, some innovations, such as financial fragmentation, represent a temporary deviation from market integration. Therefore, we propose a fourth classification, disequilibrium, as a temporal innovation resulting from financial fragmentation.

In summary, the taxonomy proposed in Figure 2-4 provides a framework through which to examine events that lead to the fragmentation of financial markets. The taxonomy extends upon internally driven process and product-based fragmenting events to include externally driven pricing-based events. This results in the three Ps of fragmentation: process, product, and pricing. Six motivating factors leading to market fragmentation presented by Tufano (1989) are used to explain internally driven innovations. Internally driven fragmenting events are classified based on their degree of innovations according to the categories proposed by Avlonitis et al. (2001). Finally, this chapter introduces new categories to supplement those presented by Tufano (1989) and Avlonitis et al. (2001) to allow for the classification of externally driven fragmenting events. Economics shocks complement the categories presented by Tufano (1989) and represent a reactionary motivation for pricing-based fragmenting events. Temporal innovations, that is, deviations from accepted equilibrium values, complement the more permanent degrees of innovations proposed by Avlonitis et al. (2001).

The remainder of this chapter further explores the different forms of fragmentation presented in Figure 2-4. This chapter identifies specific motivational factors that contribute to each fragmentation event and discusses the degree of innovation they represent. The impact these events have on market conditions, particularly their influence on liquidity and the price discovery process, is also explored. Finally, this chapter summarises the results and discusses the key points of the proposed taxonomy.

2.2 Competitive Market Fragmentation

This section focuses on what is considered to be the most widely accepted definition of fragmentation in financial markets, competitive market fragmentation. Competitive market fragmentation refers to the introduction of new exchanges, or modifications to existing exchanges, which modify how investors access liquidity. Competition of this nature splits the consumer base into distinct pools. As a result, investors are isolated from potential trading partners and are no longer able to access all available liquidity in a particular asset. The proposed taxonomy groups events into four distinct categories spanning two asset classes to investigate exchange-based fragmentation events. The two asset classes included in this study are equities and cryptocurrencies.

This section, as summarised in Figure 2-5, proposes that competitive market fragmentation events result in permanent changes to market structure. While these innovations may lead to the formation of new exchanges, these exchanges are not new services. Instead, they largely consist of modifications to existing services. New exchanges position themselves competitively in the market by offering investors improved transaction and search costs. They also help complete the market by targeting various subsets of heterogeneous investors by creating access to features that are unavailable in existing exchanges. Finally, more modern exchanges classes, such as dark pools and cryptocurrency exchanges, are capitalising on recent technological advancements such as improvements in network infrastructure and the development of distributed ledgers.

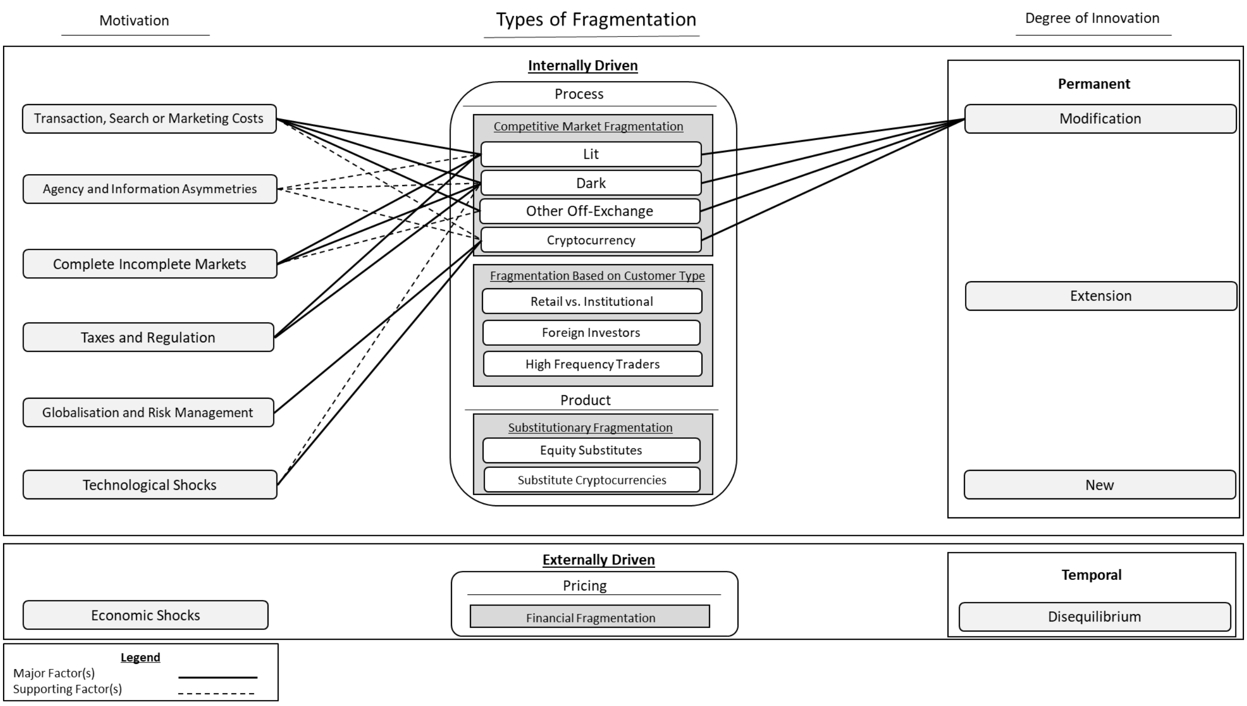

Figure 2-5: Taxonomy of Market Fragmentation (Competitive Market Fragmentation)

Section 2.2.1 discusses fragmentation in equity exchanges which are pre-trade transparent, herein referred to as lit markets. These events represent the most traditional instances of exchange-based fragmentation. Section 2.2.2 investigates instances of fragmentation in non-pre-trade transparent markets, herein referred to as dark pools. Section 2.2.3 focusses on equity markets by studying other off-exchange activities such as over-the-counter markets and hidden orders. Finally, Section 2.2.4 studies competition amongst cryptocurrency exchanges.

2.2.1 Lit Market Fragmentation

Multiple factors motivate lit market fragmentation resulting from the competition amongst equity exchanges. Section 1.1 has already discussed the influence of regulatory changes on market fragmentation so this section will focus on other factors. This section discusses existing research to support the claims that lit market fragmentation is primarily motivated by a desire to reduce transaction costs and to promote market completeness.

Transaction Costs

Many studies that form the foundation for modern fragmentation theory argue that exchanges are natural monopolies. Participants benefit from economies of scale that lower transaction costs through their superior ability to match buyers and sellers (Chowdhry & Nanda, 1991; Mendelson, 1987; Pagano, 1989). Investors gravitate towards the most liquid market resulting in a positive feedback loop which further improves liquidity in the dominant market (Pagano, 1989). Greater participation by investors leads to improvements in both the probability and speed of execution, resulting in lower search and transaction costs. This, in turn, attracts more investors and fuels further improvements in the quality of trade execution. Therefore, any innovations which lead investors to use alternative exchanges will adversely affect liquidity (Pagano, 1989).

Recent studies, however, favour fragmented markets and argue that competition amongst exchanges benefits customers as it helps lower trading costs. O'Hara and Ye (2011), using data on 265 stocks over six months in 2008, find that higher levels of fragmentation are inversely related to both transaction costs and the speed of execution. New exchanges use cost savings as a means of attracting liquidity and maintaining acceptable execution speeds for their clients. Execution speeds are critical in maintaining an active investor pool and protecting investors from adverse price changes. While the creation of competing exchanges leads to permanent changes to the landscape of the market, an inability to maintain sufficient trading volume levels can cause a reversal of these events. Lower exchange fees allow liquidity suppliers and investors to transact at prices closer to the midpoint of the bid-ask spread. Thus, cost savings materialise on exchanges through improvements in liquidity such as tighter bid-ask spreads. Monopolistic trading environments often result in non-competitive behaviour and the introduction of a competitor aids in improving trading costs in the form of tighter primary exchange bid-ask spreads as increased competition forces liquidity suppliers to improve their prices (R. H. Battalio, 1997; B. Boehmer & Boehmer, 2003; Colliard & Foucault, 2012; Foucault & Menkveld, 2008). Madhavan (1995) also finds that large traders front-run their own trades in a consolidated market resulting in greater execution costs for the average investor.

Recent regulatory changes such as the Regulation National Market System (RegNMS) in the U.S. and the Markets in Financial Instruments Directive (MiFID) in Europe have led to a resurgence in research surrounding fragmentation and transaction costs. Studies such as Degryse et al. (2015) and Gresse (2017) show that the desire to reduce transaction costs motivates innovations that contribute towards market fragmentation. Using a sample of 52 large and midcap stocks from the Amsterdam Exchange (AEX) from 2006 to 2009, Degryse et al. (2015) find that fragmentation in lit markets results in lower bid-ask spreads. However, the authors find that these improvements are largely exclusive to new exchanges. The primary exchange in the country does not experience such improvements as they do not feel the need to lower fees to remain competitive and maintain an active investor base. Therefore, the desire to lower transaction fees in order to divert investors away from the dominant exchange motivates innovations leading to the formation of new exchanges. Gresse (2017) finds similar results using a sample of large and midcap United Kingdom (U.K.) and Euronext stocks. However, unlike Degryse et al. (2015) they find that local primary exchanges experience some improvements to costs through tighter bid-ask spreads as major exchanges lower fees in an attempt maintain their dominance.

Post Trade Transparency

The completion of incomplete markets also motivates lit market fragmentation. Research on the differences in trade disclosure rules shows that because traders are heterogeneous in their trading requirements, markets will fragment to meet their demands (L. E. Harris, 1993). Madhavan (1996) argues that differences in trade disclosure rules encourage the fragmentation of investors. When trade disclosure is left to the discretion of the investor markets are more likely to fragment permanently into multiple exchanges. Conversely, markets that consist of exchanges with similar requirements surrounding trade disclosure, particularly those that require disclosure, tend to consolidate as investors gravitate to the cheapest and most liquid alternative.

Fragmentation in lit markets motivated by market completeness is separate from events motivated by the reduction in transaction costs. Madhavan (1995) finds that intraday bid-ask spreads widen upon the migration of investors to exchanges with less restrictive trade disclosure requirements. This is due to dealers facing greater levels of uncertainty resulting from the absence to potentially price adjusting information. Madhavan (1996) and de Frutos and Manzano (2005) provide support for these results, which are also consistent with the experimental findings of Bloomfield and O'Hara (1999, 2000). Bloomfield and O'Hara (1999,

2000) find that greater market transparency, most notably trade disclosure, improves market liquidity and reduces price volatility. Their findings imply that transparency increases price efficiency.

Information Asymmetry Reduction

The reduction of information asymmetry is also a contributing factor towards the fragmentation of lit markets. Existing research supports the notion of fragmentation in pre-trade transparent exchanges leading to greater adverse selection. The result is an impedance the price discovery process (Chowdhry & Nanda, 1991; Madhavan, 1995). Madhavan (1995) also proposes that differences in trade disclosure rules motivate the fragmentation of markets and that exchanges with similar requirements tend to consolidate. Greater fragmentation affords informed investors the ability to more easily conceal their trades from investors wishing to take advantage of their superior information. It also allows dealers to be less competitive. Both of these factors contribute to price volatility.

Empirical research supports the idea that greater levels of lit market fragmentation lead to less efficient prices. Critics of market fragmentation in displayed order books argue that fragmentation is inversely related to price efficiency. Bennett and Wei (2006) study 39 stocks that transfer their primary listing from a fragmented market (NASDAQ) to a consolidated market (NYSE) between 2002 and 2003 and conclude that the transition results in improvements to price efficiency and liquidity provisions. They also observe additional improvements to price efficiency through reduced volatility and a contraction of quoted, effective and realised spreads. Barclay, Hendershott, and Jones (2008) also find that consolidating orders leads to more efficient pricing. Easley et al. (1996) and Bessembinder and Kaufman (1997) use the concept of cream-skimming to explain the adverse effects on the price discovery process. They argue that the price discovery deteriorates in fragmented markets as informed investors pick off the most profitable uninformed trades.

In summary, the desire to spur competition through the offering of reduced transaction fees and search costs motivates markets to create services that lead to events of competitive market fragmentation. Opportunities which allow exchanges to cater to a unique set of investors, that is, they contribute towards completing the market, are also influential, as are changes in regulatory policy. While such events lead to the creation of new equity exchanges, such exchanges merely modify existing services and do not introduce a completely new medium of exchange.

2.2.2 Dark Market Fragmentation

Dark pools represent a modification of existing services as they are exempt from pre-trade transparency requirements. The introduction of dark pools alongside traditional pre-trade transparent exchanges is a type of competitive market fragmentation that has grown in popularity in the last decade. Section 1.1 discusses the importance of changes in regulation for the development of dark markets. Therefore, the remainder of this section focuses on other major and supporting factors.

Liquidity/Market Quality

Dark pools offer improved pricing on trades as they allow investors to transact at the midpoint of the bid-ask spread. Transacting at the midpoint saves both buyers and sellers half of the bid-ask spread when trading in dark pools compared to traditional lit exchanges. However, while dark pool participants benefit from lower transaction costs, the resulting impact on lit markets is mixed. The majority of studies argue that the benefits from dark pools come at the expense of reduced liquidity on lit exchanges.

Recent studies report mixed results surrounding the liquidity impact of dark pools. Buti, Rindi, and Werner (2017) develop a theoretical model in which traders can submit their order to either a limit order book or a dark pool. They conclude that upon the introduction of a dark pool alongside a limit order book, investor welfare, consisting of factors such as bid-ask spreads and execution speeds, increases for both retail and institutional traders. However, this effect only applies to liquid stocks. The improvements to institutional investors' welfare are consistent with the findings of previous studies such as Conrad, Johnson, and Wahal (2003). Retail traders' welfare, however, is always found to decrease. The authors find that, for liquid stocks, both limit and market orders migrate to the dark pool, resulting in tighter spreads, thereby improving transaction costs. However, competition for illiquid stocks lowers the probability of execution of limit orders and results in a widening of spreads.

Other studies present more uniformity in their results. O'Hara and Ye (2011) find a negative relationship between dark pool market shares and bid-ask spreads. Comerton-Forde and Putniņš (2015), Degryse et al. (2015), and Hatheway et al. (2017) observe that bid-ask spreads widen as dark pool market shares increase while O'Hara and Ye (2011) and Ready (2014) find the opposite. Buti et al. (2011) use 2009 data from 11 U.S. dark pools and conclude that dark pool activity exhibits a positive relationship with bid-ask spreads. The results of a time series analysis show that increases in the market share of dark pools causes bid-ask spreads to widen and negatively impacts volatility, returns, and order imbalance. Zhu (2014) models the relationship between dark pools and quoting exchanges and attributes these negative effects to informed traders. Due to their tendency to transact on the same side of the order book, informed investors have difficulty finding counterparties in dark pools. The result is a concentration of price adjusting information to traditional lit exchanges. While this leads to prices becoming more informative, any improvements to price discovery come at the cost of greater adverse selection risk and wider bid-ask spreads.

Hendershott and Mendelson (2000) reach a similar conclusion to Zhu (2014) when they study the interaction between dealer networks and passive crossing networks. They also find that any improvements in price efficiency on lit exchanges come at the expense of wider bid-ask spreads as dark pools gain market share. However, Hendershott and Mendelson (2000) attribute the result to investors who use the dealer market as a last resort. They argue that such activities coerce dealers into widening bid-ask spreads. They also propose that traders who exclusively participate in non-pre-trade transparent markets can help tighten spreads on lit exchanges. Spreads tighten, and transaction costs improve, as traders coerce informed investors into leaving lit exchanges. This leads to the opposite effect than the one previously discussed where a contraction in spreads comes at the cost of price efficiency.

Hendershott and Jones (2005) and Nimalendran and Ray (2014) provide empirical support for the former of the two outcomes previously discussed in Hendershott and Mendelson (2000). Their results are in line with the predictions outlined by Zhu (2014). Hendershott and Jones (2005) and Nimalendran and Ray (2014) find that the reduction in transparency leads to an increase in transaction costs and adverse selection on the primary exchange.[3] Dark pools reduce the primary exchange's market share as they lure investors to their alternative trading venue. Investors take with them information that is relevant to the formation of accurate trade prices as they migrate away from the primary exchange. This impedes the price discovery within the primary exchange, which primarily impacts retail investors who are less likely to have access to alternative exchanges and their corresponding liquidity pools. Competing exchanges, however, benefit from the change through a reduction in trading costs. Degryse et al. (2015) attribute this increase in adverse selection to instances of 'cream-skimming' resulting from a dark pool's ability to attract largely uninformed order flow.

[3] A primary exchange is defined as the exchange on which a stock was originally listed.

Price Discovery

Price discovery is a proxy for the levels of asymmetric information in the market. Research shows that fragmentation associated with dark markets is not associated with the dissemination of price revealing information. M. Ye (2012) extends the classical rational expectation model by Kyle (1985). They study the effects of presenting informed traders with the option of sending their trades to either a displayed limit order book, operated by a traditional exchange, or a crossing network, a particular type of dark pool. Informed investors value the ability to conceal their trade intentions from the market. Doing so allows them to realise the maximum profit from their superior information. This, in turn, motivates them to continue to generate new information which is essential to the price discovery process. By routing orders to a crossing network, informed investors protect their information at the expense of a reduction in price discovery resulting from pre-trade transparent transactions. Price discovery is impeded to a greater extent for stocks with higher fundamental value uncertainty. M. Ye (2012) concludes that informed investors will continue migrating their trades to dark liquidity pools until they are indifferent between the increased execution probability risk, they are exposed to in the crossing networks and the price impact in the traditional exchange.

Zhu (2014) develops a similar model to M. Ye (2012) but assumes that liquidity traders are exogenous in their choice of trading venue. Zhu (2014) improves on other models that exogenously fix the strategies of informed traders (Hendershott & Mendelson, 2000) or fail to consider the role asymmetric information plays regarding the value of the asset (Buti et al., 2017; Degryse, Van Achter, & Wuyts, 2009). Zhu (2014) argues that informed investors face lower execution probability in dark pools relative to uninformed investors. This occurs because orders submitted by informed investors are positively correlated with the value of the asset, and therefore each other. As a result, informed investors cluster on the heavy side of the market resulting in increased competition amongst each other for access to liquidity offered by their uninformed counterparts. This results in traditional pre-trade transparent exchanges becoming more attractive to informed investors. The price discovery process is improved as permanent price-adjusting information concentrates on the lit exchange. However, this comes at the cost of wider bid-ask spreads and greater adverse selection risk for uninformed investors. As liquidity orders are less likely to correlate with each other, dark pools become more attractive to uninformed investors. Uninformed investors are able to maintain a higher probability of execution as their trades are less likely to correlate with each other.

L. Ye (2016) extends upon Zhu (2014) to include the presence of noisy information. While their results are more in line with those of M. Ye (2012), their findings are not as one sided as M. Ye (2012) and Zhu (2014). L. Ye (2016) find that price discovery effects are largely dependent on the inherent noise levels in equity trades. In the presence of noise, L. Ye (2016) finds that the informed traders prefer to route their orders to dark pools. The result is an impediment in the price discovery process as relevant price-adjusting information is concealed from investors until after a successful transaction. In contrast, the presence of low levels of noise where the level of information risk is low causses informed to prefer traditional pre-trade transparent exchanges over dark pools. This result coincides with that of Zhu (2014) and leads to an improvement in price discovery. Unlike the model presented by M. Ye (2012), L. Ye (2016) model also allows uninformed traders to choose between exchanges. Removing this choice aligns the results with that of M. Ye (2012).

Comerton-Forde and Putniņš (2015) provide empirical support for Zhu (2014) in their study on the impact of dark liquidity on the price discovery process. They use Australian data from the ASX All Ordinaries index from 1 February 2008 to 30 October 2011 and focus on the Australian Stock Exchange (ASX) and Chi-X exchanges. Comerton-Forde and Putniņš (2015) reveal that aggregate price discovery is impeded, and prices become less efficient as order flow migrates from lit to dark trading venues. However, this effect is only realised when the proportion of non-block dark trading consists of 10% or more of all transactional volume. Lower price efficiency disincentivises informed traders from participating in costly information acquisition. This, in turn, leads to a further reduction in the informational efficiency of prices. As uninformed trading in the lit market reduces disproportionally, high levels of dark trading also lead to increases in adverse selection and a widening of bid-ask spreads in the primary lit market. These results are corroborated by Hatheway et al. (2017), whose study consists of 59 NYSE and 57 NASDAQ stocks over three months beginning January 3rd 2011. In contrast, Comerton-Forde and Putniņš (2015) find that dark liquidity can improve price discovery within the primary exchange, which is beneficial for retail investors when the market share of dark liquidity is below 10%. The opposite effects surrounding the 10% dark market share threshold imply that price discovery is an increasing concave function (Comerton-Forde & Putniņš, 2015).

In summary, dark pools have grown in popularity due to their ability to offer reduced transaction costs for investors. Regulatory changes play a pivotal role in dark market fragmentation due to their focus on investor protection through policies such as the best-execution rule (see Section 1.1). Dark pools also help complete markets by providing investors with additional trading options regarding the dissemination of trade information. Recent technological developments also support growth in these markets. As dark pools operate in a black box, they are devoid of any human interference when matching orders. Matching orders at such a large scale would not be possible without improvements to computing speeds as well as networks which allow for remote electronic order submission. The intent to reduce information asymmetry is not a leading motivational factor in the formation of dark pools. By their very nature, dark pools will attract some level of informed activity from the pre-trade transparent exchange (see Figure 2-5).

2.2.3 Other Off-Exchange

This section focusses on activities, apart from dark pools, that remove liquidity from the centre limit order book (CLOB). We investigate over-the-counter transactions and hidden orders. While these activities can resemble dark pools, they operate with slightly greater levels of pre-trade transparency. Over-the-counter transactions experience greater pre-trade transparency than their dark counterparts as they require the involvement of a third party who is aware of the request. Hidden orders can allow for a portion of the order to be published to the CLOB. As a result, neither of these two options operate entirely within a black box.

In summary, the desire to reduce transaction costs is a driving factor behind the development of off-exchange liquidity pools. Unlike traditional CLOB transactions, off-order book trades allow investors to negotiate prices. Off-exchange activity is also motivated market completeness as brokers can locate unadvertised liquidity. Access to unadvertised liquidity also comes with the added benefits of reduced search costs and investors take advantage of brokers' investor networks. As with dark pools, the intent to reduce information asymmetry is not a leading motivational factor behind the formation of off-exchange liquidity pools. By design, off-exchange liquidity pools will attract some level of informed activity (see Figure 2-5).

2.2.3.1 Over-the-counter/Upstairs Market

Many stock exchanges today, including the Australian Stock Exchange (ASX), New York Stock Exchange (NYSE) and the Toronto Stock Exchange (TSX), offer investors the flexibility of transacting in either the downstairs or the upstairs market. The downstairs market is exclusively automated and order-driven, operating within the central limit order book (CLOB) which is visible to all potential participants. However, the upstairs market consists largely of broker-dealers who operate outside the CLOB. The result is a process-oriented innovation which leads to the fragmentation of the market where clients transact in the liquidity pool they feel is most suitable to their trade requirements. Innovation leading to the fragmentation of investors as a permanent modification to existing services. The upstairs market operates on many of the same principles as the downstairs market. However, it is not considered an extension of traditional exchanges as it does not add to and maintain the existing features of the downstairs market. By operating on the same principles as the traditional downstairs market, it is not a new innovation, rather an extending modification.

The search for lower transactions costs predominately motivates the innovation of upstairs markets. This section presents several studies that argue that investors save money when conducting certain trades in the upstairs market when compared to the downstairs market (Grossman, 1992; Madhavan & Cheng, 1997; Seppi, 1990; B. F. Smith, Turnbull, & White, 2001). Upstairs market trades predominately consist of large block over-the-counter (OTC) transactions where prices are negotiated amongst trading parties (Madhavan & Cheng, 1997). Broker-dealers choose to execute client orders against their own account, acting as a principal to one side of the trade, or act on behalf by the client by 'shopping' the order and searching for interested counterparties. Executing trades outside of the displayed order book allows for all shares to transact at a single price. Therefore, investors are not exposed to predatory trading activities as they exhaust the offerings at multiple levels of the order book.

Involving a third party means that upstairs market participants are not subject to the same levels of anonymity as their downstairs counterparts. However, by operating outside the CLOB, they circumvent pre-trade transparency requirements and can conceal their intentions from the market in the event that the transaction is not successful. This implies that the goal of reducing information asymmetry is not a motivating factor behind the formation of upstairs markets. Excluding orders, whether successful or not, from the centralised display order book widens the level of information asymmetry as not all investors are privy to the knowledge of the existence of such orders. As a result, they are unable to infer the intentions behind the orders and react accordingly in their trading activities.

Seppi (1990) is a seminal work studying competition between specialists in the downstairs market and brokers in the upstairs market. The model consists of a multi-period market and focusses on the existence of equilibria when there is information-based block trading. Participants in the model include the specialists and dealers mentioned above as well as a single large investor, who may be informed or uninformed, and several small noise traders. Seppi (1990) concludes that brokers can use the lack of anonymity in the upstairs market to their advantage. Informed and uninformed traders can be identified based on their reputation and brokers use this advantage to only trade with uninformed investors. This occurs as there exists a separating equilibrium for block sizes below a critical threshold. Markets fragment as uninformed investors choose to transact large blocks with a dealer while informed investors favour breaking the block into several smaller components using market orders on the exchange to execute them.[4] Also, by imposing additional restriction to the trade including the requirement for the investor to not trade the stock within a certain period of time, the dealer can further identify the uninformed nature of the trade.

Grossman (1992) also develops a model involving specialists and brokers in downstairs and upstairs markets, respectively. Grossman's (1992) model focusses on how brokers act as a repository for information pertaining to unexpressed liquidity. Knowledge of unadvertised liquidity gives brokers' clients access to deeper liquidity pools when compared to the CLOB. Brokers attract clients by using this information to their advantage. While both brokers and specialists have access to information regarding orders in their respective markets, only brokers know the identity of the investors placing the orders. Unlike specialists, this allows them to maintain contact with clients keep a record of potential future trade counterparties. However, the deeper liquidity pool in the upstairs market comes at the disadvantage of having to negotiate prices with no guarantee that they will transact at a price that is as, if not more, favourable than the one on the exchange.

Madhavan and Cheng (1997) find empirical support for Seppi (1990) in their analysis of block trades of Dow Jones Industrial Average (DJIA) stock on the NYSE. They study the role upstairs and downstairs markets play in liquidity provision and find that uninformed investors do indeed transact in the upstairs market when they can successfully express their uninformed status. The ability to isolate for uninformed orders encourages investors to supply liquidity. The upstairs market is effective in executing large liquidity-driven orders at a lower cost than those executed on the CLOB. Such improvements to execution costs suggest that reducing transaction fees is a significant motivating factor in the development of upstairs markets. However, in contrast to Grossman's (1992) model, Madhavan and Cheng

[4] Some components can also be directed towards the upstairs market as well.

(1997) find that specialists and other investors trading on the exchange provide a similar level of liquidity compared to the upstairs market. As a result, the two markets are similar in terms of their permanent price changes.

B. F. Smith et al. (2001) perform a similar analysis to Madhavan and Cheng (1997) using Toronto Stock Exchange (TSX) data. They also find support for Seppi (1990) in that the upstairs market is effective in identifying and executing large uninformed orders whose motivations are liquidity driven. They also find that the upstairs market attracts trading in less liquid stocks. Bessembinder and Venkataraman (2004) present two more studies in support of Seppi (1990) using Helsinki Stock Exchange (OMXH) and Paris Bourse data, respectively. They provide further evidence that upstairs trades are less informed than their CLOB counterparts and execute at a lower cost, with Bessembinder and Venkataraman (2004) showing that upstairs execution costs are 65% lower than those in the CLOB.

B. F. Smith et al. (2001) also show support for the model developed by Grossman (1992). They find that a substantial number of upstairs market trades transact at prices that are more favourable than those available in the downstairs market. Grossman (1992) argues that this is a result of upstairs market dealers having greater access to liquidity, particularly unexpressed liquidity, due to their knowledge of customer identities and previous trading activity. This provides evidence that the competition of incomplete markets is a supporting motivational factor behind this type of off-exchange fragmentation. While upstairs orders may not initially interact with the CLOB, investors maintain the option to access that investor pool once all other off-exchange counterparty choices are exhausted. Burdett and O'hara (1987) and Keim and Madhavan (1996) concur with Grossman (1992) as their models also indicate that having the ability to locate several trade counterparties results in a more favourable trading price. Grammig, Melvin, and Schlag (2001) provide additional empirical support for Grossman (1992) in their study of the German stock market. They compare traffic across IBIS, an anonymous limit order book that operates as a proxy for the downstairs market in Grossman (1992), and the floor-based Frankfurt Stock Exchange, a non-anonymous and trading system that operates as a proxy for the upstairs market. They find that the bid-ask spread charged by market makers is noticeably lower in the Frankfurt Stock Exchange compared to IBIS, and as a result, the upstairs market proxy offers more favourable prices.

Unlike the previous studies, Fong, Swan, and Madhavan (2001) find that upstairs market activity is driven by the needs of the investor and the characteristics of the individual markets, as opposed to a broker's preferences and liquidity provisions. Using Australian Stock

Exchange (ASX) data, they find that two factors largely influence trades that occur away from the exchange. First, the presence of institutional traders steers activity away from the exchange as they attempt to minimise the price impact felt from transacting large orders. Second, trading activity migrates towards the upstairs markets if the exchange is not sufficiently liquid and displays high bid-ask spreads with shallow depth. B. F. Smith et al. (2001) also find a positive correlation between upstairs market volume and CLOB bid-ask spreads. Similar to Fong et al. (2001), Friederich and Payne (2007) find that participation in the CLOB is low when the market is illiquid in terms of depth and spreads. Using data from the London Stock Exchange (LSE) where broker-dealers firms compete for liquidity with the CLOB, they also find that both high asymmetric information risk and high execution risk drives investors toward the upstairs market.

There is also evidence to support the informational effect of trading in the upstairs market. Kraus and Stoll (1972) investigate the price impact of large trades and find that block trading does indeed affect the market. They find that block trades can result in both an informational effect on prices, whereby the changes are permanent and pertain to information revealed regarding the stock's fundamental value, as well as a distributional effect, in that price changes are temporary and as a result of order flow. Seppi (1990) and Grossman (1992) suggest that upstairs market trades have a lower informational effect than downstairs trades as they largely consist of uninformed liquidity-driven orders made by uninformed investors. B. F. Smith et al. (2001), Booth, Lin, Martikainen, and Tse (2002) and Bessembinder and Venkataraman (2004) support this and find that upstairs trades have a significantly lower price impact (informational effect) than downstairs trades. Using vector error correction models (VECM) Booth et al. (2002) also find that a large percentage of the price discovery is conducted within the CLOB, providing further evidence of the informed nature of CLOB trades. Madhavan and Cheng (1997) find that permanent price changes are similar for both upstairs and downstairs market trades on the NYSE.

Westerholm (2009) uses data from the Helsinki Stock Exchange (OMXH) and benefits from having access to a dataset with unique identifiers for institutional investors. The study further confirms Grossman (1992), finding that upstairs market trading is largely uninformed and able to access unexpressed liquidity. As a result, the information effect of upstairs trades is lower than those that originate from the exchange. Westerholm (2009) also finds investors rely more on the upstairs market when the CLOB present investors with high transaction costs, high volatility, and low liquidity. A later study by Rose (2014) uses Australian Stock

Exchange (ASX) data and finds that the informational effect of trades is noticeably higher in the CLOB. This supports Seppi (1990) and Rose (2014) and implies that uninformed investors activity migrates to the upstairs market. Rose (2014) correlates higher upstairs market volume with lower transaction costs, higher volatility, and greater liquidity. This shows that, except for volatility, fragmentation instituted by the upstairs market has a predominately positive impact on traditional exchanges.

2.2.3.2 Hidden Orders

Hidden orders allow traders to hide the entirety or a portion of their order from the market. Their use fragments the displayed (visible/lit) order book and removes accessibility to potentially price adjusting information. As a result, they are similar to upstairs market orders in that they are not motivated by the desire to correct for instances of information asymmetry. Hidden orders are now found across many equity markets including the Australian Stock Exchange (ASX), Euronext, the New York Stock Exchange (NYSE) and the Toronto Stock Exchange (TSX), to name a few. However, the level of anonymity is not uniform across all markets. For example, Euronext requires investors to employ the use of iceberg orders when concealing liquidity. Iceberg orders reveal only a portion of a limit order which, much like their namesake, obfuscate their true size. Other exchanges use the time priority, or lack thereof, of hidden orders to promote transparency and encourage traders to reveal liquidity. This is achieved by delaying the execution of hidden orders until after all displayed liquidity orders at that price level have been exhausted. As a result, the taxonomy classifies hidden orders as a modification of traditional displayed liquidity.

As hidden orders are pre-trade transparent, they represent a form of on-exchange dark liquidity. True market depths and best prices are obscured leaving traders unaware as to the exact state of the order book. Once again, this increases the level of information asymmetry in the market. Compounding in the distortion occurs as hidden orders discourage potential counterparties from entering the market. L. Harris (1997) introduces the concept of ‘reactive’ traders who monitor the order book until presented with opportune trading conditions. L. Harris (1997) implies that excess use of hidden orders impedes a market’s capacity to attract previously unadvertised liquidity. Bessembinder, Panayides, and Venkataraman (2009) find support for this in their study of Euronext stocks. They conclude that hidden orders are associated with a decrease in the probability that an order will be fully executed, in addition to longer order completion times. The implication is that hidden order use lowers overall transactional volume and prevents traders from participating in the market (Harris, 1997).

In contrast, Moinas (2010) finds that excess limit order usage reduces execution probability as defensive traders cancel their existing positions. Anand and Weaver (2004) find that the expulsions and reintroduction of hidden order on the TSX in 1996 and 2002, respectively, has no impact in quoted depth. This suggests that hidden order represent liquidity that would otherwise not be accessible and is consistent with the findings of Grossman (1992). Grossman (1992) argues that the upstairs market, which operates outside the displayed order book similarly to hidden orders, is also a repository for unexpressed liquidity. This, in turn, provides the support that, similar to upstairs market transactions, hidden orders contribute to completing incomplete markets by expanding the pool of potential counterparties.

Other traders take a more aggressive position and actively search for hidden liquidity. They submit limit orders in the hopes of executing against hidden orders J Hasbrouck and Saar (2002). If after a few seconds a counterparty is not found the investor cancels their limit order, after which they repeat the process. If hidden liquidity is partially exposed through the use of iceberg orders, detecting such orders causes traders to demand more liquidity than is advertised at the best price (De Winne & D'hondt, 2007; Pardo & Pascual, 2012).

While the use of hidden orders increases the likelihood of traders making mistakes regarding perceived demand and supply of shares, it is a valuable tactic for those looking to mask their activities. Should other market participants infer that a trader possesses superior private information upon submitting a limit order, they may be encouraged to either cancel standing limit orders or refrain from submitting new ones (L. Harris, 1997). Even worse, they may decide to 'front-run' the order by submitting their own at a more favourable price. L. Harris (1997) argues that the larger the exchange tick-size, the less likely it is that exposed orders will be front-run due to the cost of doing so. Using Australian Stock Exchange (ASX) data, Aitken, Berkman, and Mak (2001) confirm that larger tick sizes encourage investors to expose their positions.

Moinas (2010) and Buti and Rindi (2013) provide support for the findings of Harris (1996). In their model, Moinas (2010) confirms that fast traders can benefit from using new public information faster than a limit order trader can cancel their now mispriced order. Moinas (2010) and Buti and Rindi (2013) find that both informed and uninformed liquidity traders can reduce transaction costs by using hidden orders to minimise the impact of their trading activities. However, Pardo and Pascual (2012) find that the execution of iceberg orders on the Spanish Stock Exchange do not have adverse effects on liquidity or volatility. The lack of price impact suggests that these orders are largely uninformative.

2.2.4 Cryptocurrency Exchanges

Bitcoin (BTC), the world's first modern-day cryptocurrency, launched in 2009 following the release of a 2008 whitepaper published under the name Satoshi Nakamoto. Advancements in networking technology fuelled Bitcoin's key market innovation, leading to the creation of its decentralised and distributed structure. Bitcoin distinguishes itself from other previously developed digital and virtual currencies by being the first currency to operate under such a decentralised structure.

Cryptocurrency exchanges operate under many of the same principles as lit equity exchanges but make some modifications due to the nature of the product itself, which we classify as a new innovation (see Section 2.4.2). Some exchanges execute customer orders using deposits that customers have made into the exchange. Others operate as a matching platform, similar to a traditional equity exchange, where customers submit buy and sell limit orders, and trades execute upon the identification of a suitable counterparty. Most exchanges also offer continuous trading throughout the day, but the highest levels of activity typically occur during local equity market trading hours (Dyhrberg, Foley, & Svec, 2018). Higher levels of volatility and lower spreads during local trading hours implies the most trades are executed manually by retail investors as opposed to trading algorithms (Dyhrberg et al., 2018).

While cryptocurrency exchanges represent a modification to existing lit equity exchange structures, we classify them separately from the previously mentioned equity-based forms of competitive market fragmentation. This allows for comparison in the motivating factors behind competitive market fragmentation across investor pools and asset classes. In this section we find the creation of new cryptocurrency exchanges is largely motivated by globalisation and risk management, and the technological advances that allow for such changes. However, the creation of new lit equity exchanges, with which they share many characteristics, are motivated by changes in regulations that allow for a reduction in transaction and search costs achieved through market completion.

On March 17, 2010, the first Bitcoin exchange, BitcoinMarket.com, began operations. It allowed users to purchase and redeem Bitcoin, using PayPal as a means of transferring value between Bitcoin and fiat currencies. These actions would not be possible without recent technological advancements in online payments and the development of blockchain-based distributed ledgers. Technological shocks are a significant motivating factor behind fragmentation among cryptocurrency exchanges. Bitcoin and other cryptocurrency transactions have since evolved from a monopolistic market dominated by a single exchange to a fragmented market with over 246 major exchanges in operation as of March 2019.[5]

In December 2013, cryptocurrency trading was more consolidated around a single currency with USD trading representing 82.2% of all transactional volume (Brandvold, Molnár, Vagstad, & Valstad, 2015). Figure 2-6 displays the market share, according to trading volume, by the top 18 cryptocurrency exchanges as of January 2019. P2pb2bUSD is a peer-to-peer exchange and represents the dominant means of transacting with 26% market share followed by bitstampUSD with 13%, and krakenUSD, coinbankGBP and krakenEUR all with 7% each. The majority of transactional volume, 54%, is completed with U.S. dollars followed by the Japanese Yen, Euro, and British Pound Sterling with 18%, 13%, and 8%, respectively (Figure 2-7). The fragmentation of orders across a wide range of sovereign currencies represents a major change in international cryptocurrency trading. Four exchanges (p2pb2bUSD, bitstampUSD, krakenUSD, and coinsbitioUSD) are responsible for 51% of the 54% market share of U.S. dollar transactions. This shows that the cryptocurrency exchange market, while fragmented overall, is dominated by a handful of major exchanges. Since many exchanges also transact across multiple currencies, this study proposes globalisation also to be a motivating factor behind their creation, resulting in the subsequent fragmentation of cryptocurrency markets. Doing so also reduces search costs for traders as they need only participate in a single exchange to access liquidity from counterparties across the globe.

However, formal exchanges are not the only places to trade cryptocurrencies. Fink and Johann (2014) find that of the total daily number of Bitcoin transactions, only 13% occur through market exchanges. The results originate from comparing the total volume in the Bitcoin network to trading volume on exchanges. Most transactions are as a result of direct trading between Bitcoin users.

[5] According to coinmarketcap.com

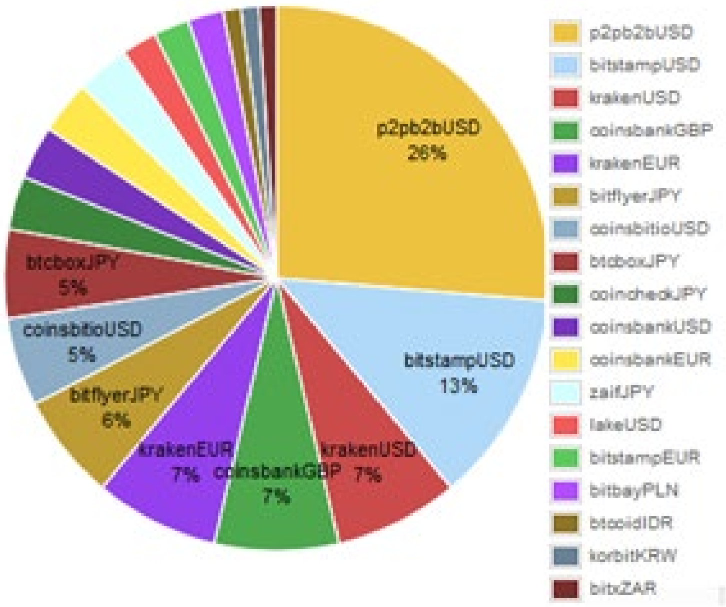

Figure 2-6: Cryptocurrency Volume Distribution (Exchange)

Source: Bitcoincharts.com (March 2019)

Exchange Survival

The state of cryptocurrency exchanges is not stagnant. Rather, it involves the formation and closure of several exchanges over time. Exchanges close for various reasons including illiquidity, fraud and theft, among others. Moore and Christin (2013) are among the first to research Bitcoin exchanges. They gather data on 40 different markets and study the factors that influence their sustainability. Of the 40 exchanges included in the study, they find that 18 of those exchanges ceased operations during the three-year study period. Of the 11 exchanges for which Moore and Christin (2013) were able to retrieve information regarding reimbursement, six of exchange closures resulted in customers losing the balances contained within their accounts, with the most famous closure being Mt. Gox. Mt. Gox is widely viewed as the first major Bitcoin exchange and accounts for roughly 80% of all trading activity during the early stages of the Bitcoin trading (Fink & Johann, 2014). The exchange filed for bankruptcy in February 2014 following the revelation of the theft of USD 350 million worth of Bitcoins from the exchange.

In support of the theory presented by Pagano (1989), Moore and Christin (2013) find that exchanges which maintain healthy levels of transactional volume are most likely to continue operating. These exchanges thrive as customers value the ability to transact quickly and finding a suitable counterparty in a timely fashion is easier when presented with a larger investor pool. Technological advancements provide critical support in improving the timeliness of transactions.

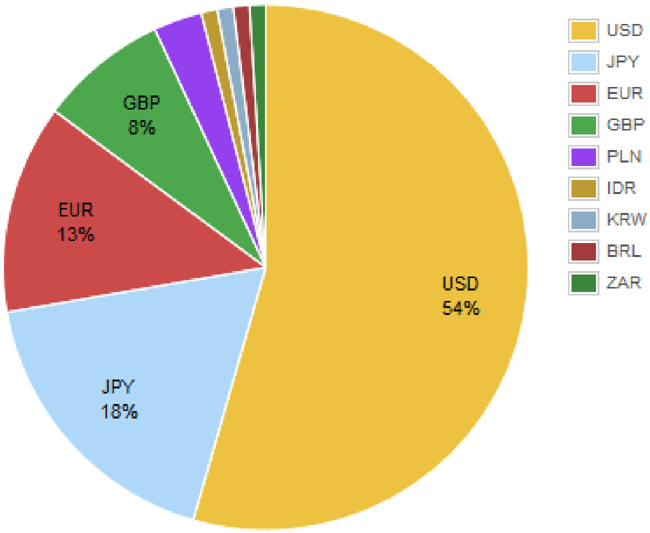

Figure 2-7: Cryptocurrency Volume Distribution (Fiat Currency)

Source: Bitcoincharts.com (March 2019)

However, Moore and Christin (2013) find that operating a popular exchange attracts the attention of criminals as popular exchanges are more likely to experience security breaches. Fraudulent activity is another factor responsible for the closure of a Bitcoin exchange. This provides further support that technological shocks are highly motivational in the formation of new exchanges. Exchange operators use advancements in security technology as a means of promoting themselves and differentiating their offerings from competitors.

Price Discovery

Fink and Johann (2014) study the pricing dynamics and their relation to the microstructure of Bitcoin markets. The authors focus on the following major exchanges, with their respective currencies presented in parentheses, to determine the extent to which they contribute to price discovery: Bitstamp (USD), Btce (USD and EUR), Btcn (CNY) and Mt. Gox (USD and EUR). Using a vector-error-correction-model (VECM), they conclude that before the bankruptcy of Mt. Gox (nearly) all exchanges have at least a 10% level of influence on the prices of their competitors. The one exception to this is Mt. Gox (USD) which does not appear to be noticeably influenced by any of its competitors. The absence of external influences leads to the conclusion that they are a price leader. Being the market leader in transactional volume at the time is consistent with theory by Hasbrouck (1995) who argues that the dominant exchange is the source of the majority of price forming information. New exchanges contribute to the process of maintaining efficient price levels across cryptocurrencies. Therefore, reductions to information asymmetry play a supporting role in motivating exchange-based fragmentation in cryptocurrency markets.

Adapting Gonzalo and Granger's (1995) component share (CS) measure Fink and Johann (2014) find confirmation that Mt. Gox (USD) dominates its competitors in terms of its contribution of permanent price adjusting information. Mt. Gox (USD) displayed a CS of 33.14 %, implying that the other exchanges adjust their prices to the information presented by the dominant exchange. Fink and Johann (2014) exclude results on Hasbrouck's (1995) information share (IS) from analysis as the large discrepancy between lower and upper bounds do not allow for drawing of dependable interpretation.

Brandvold et al. (2015) also focus on price discovery in Bitcoin exchanges. They select five major exchanges as well as two minor ones in an attempt to account for differences in behaviour resulting from exchange size. The major exchanges included in the study are Bitfinex, Bitstamp, Btce, Btcn and Mt. Gox, and all but Btcn trade in USD currency pairs; Btcn is a Chinese Yuan exchange. Except for Bitfinex, these exchanges match those used in Fink and Johann (2014), though the latter study also includes some Euro pairs as well. The two minor cryptocurrency exchanges are the Canadian Virtex and the Polish Bitcurex exchanges and, while smaller, are still apart of the ten largest exchanges at the time of the study.

Brandvold et al. (2015) find that Btce and Mt. Gox prices are more correlated future market returns compared to past market returns. Correlations with future returns indicates that Btce and Mt. Gox are price leaders. Btce and Mt. Gox transactions also trade at more informative price points. Positive covariances between fundamental price changes and idiosyncratic shocks, the basis for the IS measurement, indicate price informativeness. Mt. Gox was the overall leader with a starting IS of 0.667. This result at least partially conforms with the findings of Fink and Johann (2014) who also find Mt. Gox to be a price leader. Two of the three foreign currency pairs do not lead the market in terms of correlation with future returns with Virtex and Btcn proving themselves to be price followers. However, Btcn saw its IS increase from 0.040 in April 2013 to 0.325 in December 2013 as Chinese firms began to accept Bitcoin as payment. This figure would subsequently drop to 0.124 following the Chinese government's ban on such payments in January 2014, thus providing further support for Madhavan (1995) who states that the price discovery occurs in the most dominant and active exchanges.

In summary, recent technological advancements in online payments and the development of distributed ledgers, that is, ledgers relying on blockchain technology, motivate innovation leading to the formation of new cryptocurrency exchanges. Globalisation is also a motivating factor as investors continually need only participate in a single exchange to access liquidity from counterparties across the globe. Reducing search costs is a supporting motivational factor behind new exchange innovations and is realised through the globalisation of investor networks. Globalisation also brings with it the added benefit of reduced information asymmetry through the consolidation of international investors onto a single trading platform. However, exchanges continue to operate distinct order books based on unique fiat currencies (see Figure 2-7).

2.3 Fragmentation Based on Customer Types

Fragmentation occurs within markets when exchanges differentiate between investor classes. While many exchanges attempt to cater to as wide an array of investors as possible, other actively isolate different groups of investors. Some markets differentiate between retail and institutional liquidity while other may restrict the use of automated trading software. Sometimes the fragmentation of investors is not intentional. Firms must take explicit actions to consolidate geographically diverse investors through international cross-listing and expand their investor pool. Investors choose to trade in markets with varying degrees of customer-based fragmentation as no single market can serve the interests of all types of investors. For example, institutional investors employing passive trading strategies may be interested in concealing their intentions from the market. Retail investors, on the other hand, might be motivated by minimising transaction costs and investors protection policies that protect them from predatory traders. In this section, we explore various forms of customer-based fragmentation and classify the innovations leading to such events. The driving factors behind customer-based fragmentations are summarised in Figure 2-8 below.

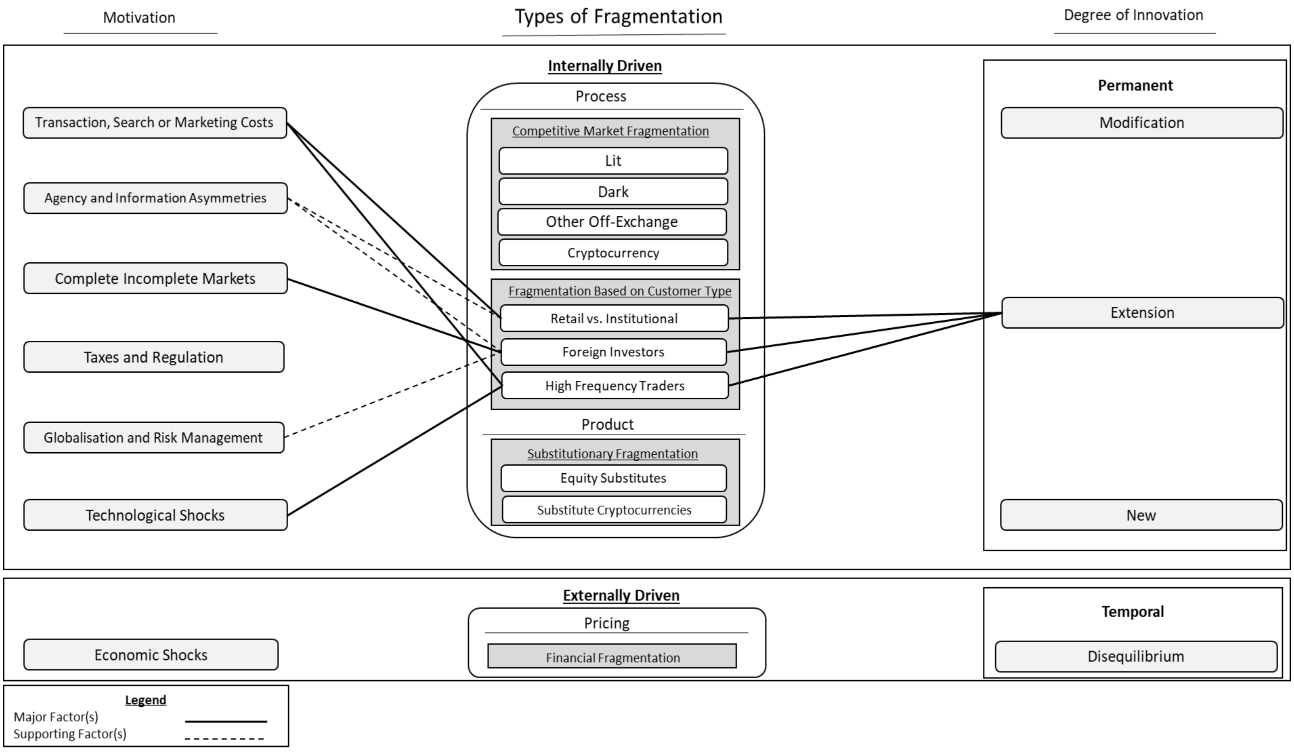

Figure 2-8: Taxonomy of Market Fragmentation (Fragmentation Based on Customer Type)

The taxonomy in Figure 2-8 depicts that fragmentation of investors into distinct liquidity pools based on customer type is an extension of existing services. Exchanges distinguish between clients based on their level of expertise (retails vs. institutional investors), location (foreign investors), and use of technology (high-frequency traders). Regardless of the customer type, these investors continue accessing liquidity like traditional equity market participants. However, due to a distinguishing feature, they are given the option to access liquidity in a manner that is unique to them. That is, they are granted superior protection against adverse selection risk or can execute transactions at a greater velocity. Policies that reduce transaction fees motivate markets to fragment customers based on unique characteristics. Technological advancements fragment customers based on their execution speed without the need for a unique order book. Market completeness is also a driving force behind the desire to allow foreign investors access to local equities. Doing so increases the level of oversight and reduces information asymmetry by consolidating information from a wider investor pool.

2.3.1 Retail vs. Institutional

Financial exchanges promote fragmentation in investor classes when they limit access to liquidity to investors that fall within specific guidelines. One particular investor class that exchanges choose to isolate from general liquidity pools are retail investors. Exchanges offer liquidity providers the option to advertise trading opportunities exclusively to investors who trade on their own accord using personal accounts. Retail investors are generally considered to be less informed compared to institutional investors. Retail investors have a limited capacity to anticipate stock demand as well as formulate high-quality private information regarding fundamental asset valuation. Liquidity providers find this desirable as executing retail trades makes it easier for them to maintain a neutral level of market exposure. These practices are extensions to existing services offered by equity exchanges. Investors have the option to continue trading within the standard, advertised, order book or divert their transactions to a protected order book. Such policies fragment the market as they create liquidity pools from which some investors are isolated, while other investors maintain access to the consolidated order book.

Retails liquidity programs (RLPs), also commonly referred to as retail price improvement programs (RPIs), are a form of market structure policy that promotes the fragmentation of retail investor liquidity within quote-driven and competitive exchanges (Chordia & Subrahmanyam, 1995; Kandel & Marx, 1999; Parlour & Rajan, 2003). They encourage the migration and isolation of retail activity by offering improvements to transaction costs compared to trades submitted to the consolidated order book. In order to submit a limit order to the RLP, liquidity providers must offer retail investors the opportunity to transact at prices that improve upon the best bid and offer prices available in the standard order book. Retail brokers are also charged lower fees by exchanges for routing client orders to RLPs and benefit from executing small orders which are typically balanced evenly on both sides of the other book. Therefore, a desire to reduce transaction costs for retail investors and liquidity providers motivates innovations that lead to the separation of retails and institutional orders. Several exchanges across the globe have adopted RLPs including Alpha Exchange (2011) and Aequitas (2015) in Canada, BATS (2012) and NASDAQ (2013) in the US, and the NYSE Euronext (2012) in Europe.

RLPs are closely related to dark pools as they traditionally operate without pre-trade transparency. Trade prices and quantities are not publicly advertised in the absence of pre-trade transparency rules. As a result, trade information is only made available following a successful transaction. One reason for operating outside of the advertised order book is that it allows for liquidity providers to offer improved prices without the need to conform to tick size restrictions. Exemptions from tick size restrictions are particularly useful when bid-ask spreads span a single tick. Price improvements would not be feasible without the circumvention of such restrictions. Early research into payment for order flow argues that the practice is only viable given tick size limitations and would disappear should the tick size reduce to zero (Chordia & Subrahmanyam, 1995; Kandel & Marx, 1999; Parlour & Rajan, 2003). However, not all researchers agree, as R. Battalio and Holden (2001) show that payment for order flow endures the introduction of decimalisation.

Theory on order flow segmentation focusses on the routing decisions of brokers. Parlour and Rajan (2003) study the phenomenon surrounding brokers who are willing to pay for order flow. Their model finds that payment for order flow leads to wider bid-ask spreads as brokers attempt to recuperate losses resulting from said payments. Payment for order flow also leads to an increase in transaction costs for market makers which has an unfavourable effect on market quality. R. Battalio and Holden (2001) do not predict such a one-sided outcome. They find that the order flow internalisation is contingent on the degree of competitiveness of the broker. Therefore, while cost reduction motivates the creation of programs that separate retail liquidity from the consolidated pool, research shows that the intention does not always align itself with the outcome. R. H. Battalio (1997) provides empirical evidence that transaction costs improve upon implementation of these changes. However, Bloomfield and O'Hara (1998) provide experimental results that contrast these findings and align themselves more the theoretical results presented by Parlour and Rajan (2003).

R. H. Battalio (1997) studies the events surrounding the entry of a third market broker-dealer who focusses on purchasing and executing retail investor orders. The author finds that bid-ask spreads improve upon the firm’s entry into the market and that the fragmentation of such retail trades did not result in any significant adverse effects on market liquidity. The results also show that changes to adverse selection risk are not economically significant as a result of retail order fragmentation. In contrast, Bloomfield and O'Hara (1998) use an experimental analysis to show that payment for order flow leads to wider bid-ask spreads.

The theoretical dark pool model of Zhu (2014) is related to the existence of RLPs as RLPs often operate without pre-trade transparency. The Zhu (2014) model also finds that, like RLPs, dark pools incentivises the segmentation of informed and uninformed orders flow. Zhu (2014) predicts that the migration of uninformed trades to a separate liquidity pool improves price discovery on the traditional exchange through the concentration of informed trading. However, such benefits come at the cost of reduced liquidity as market makers are discouraged from participating with increasingly knowledgeable counterparties. Boulatov and George (2013) also find that dark trading increases the informative of prices as the competition among informed traders intensifies. However, unlike Zhu (2014), they find that segregation of informed and uninformed investors improves liquidity.

Studies that distinguish between and measure the contributions of institutional versus retail order flow on market conditions help gain empirical insight into the effects of such investor isolation programs. Institutional investors are arguably more rational and well-informed than retail investors Aggarwal and Rao (1990). Easley et al. (1996) contend that retail order isolation can improve price discovery on exchanges. They find that the informational content of NYSE trades far exceeds those of the regional Cincinnati Stock Exchange. As a result, retail order isolation is at least partially motivated by a desire to reduce information asymmetries amongst investors by improving the quality of signals conveyed by stock prices. Easley et al. (1996) attribute this to the NYSE's ability to internalise and absorb retail order flow, thus fragmenting the market to isolate informed and uninformed order pools. Chordia and Subrahmanyam (1995) also find that orders diverted from the NYSE through payment for order flow activities are less informed. The implication is that payment for order flow is often used to cream-skim the most profitable orders from exchanges. E. Boehmer and Kelley (2009) later corroborate these findings when they find that institutional trading, which is generally considered to be informed, plays a vital role in price discovery. Using NYSE listed stocks from 1983 to 2004, they find that institutional investment is positively related to the informational efficiency of prices. Griffin, Harris, and Topaloglu (2003) also find a strong positive relationship between institutional trading volume and daily stock returns.

Institutional investors are recognised as being more informed due to their superior ability to gather private information. However, recent studies argue that retail investors are becoming more informed. Kaniel, Saar, and Titman (2008) and Kelley and Tetlock (2013) propose that retail trades are beginning to contain more information regarding future returns Kaniel et al. (2008) find a positive correlation between short term returns and retail investor trading volume. Kelley and Tetlock (2013) also find a positive relationship between future stock returns and the imbalance of limit and market orders for retail investors. The imbalance is indicative of the informational content of retail market orders. This may raise doubt into information asymmetry reduction being a supporting motivational factor in the emergence of instances of retail order fragmentation. However, the majority of the research discussed in this section supports the notion.

In summary, isolating retail investor orders from institutional orders extends upon the existing services offered by equity exchanges. The desire to protect uninformed investors from predatory traders motivates innovation, leading to fragmentation based on perceived levels of investor expertise. An increased concentration of informed trading activity leads to more informative transaction prices. This, in turn, reduces levels of information asymmetry, though is not necessarily the primary goal of such innovations (see Figure 2-8).

2.3.2 Foreign Investors (International Cross Listing)

When firms cross-list their shares on foreign stock exchanges, they fragment the market into distinct liquidity pools based on geographic location. However, this also has the effect of creating a more complete market. New subsets of investors can now apply their expertise regarding a particular stock, thereby contributing to market efficiency.

Cross-listing shares in overseas markets is not a new occurrence. Since the 1980s, firms have chosen to have their shares represented on markets outside of their respective countries. The United States (U.S.) and the United Kingdom (U.K.) are amongst the most popular choices. This choice is internally driven as firms make the conscious decision to cross-list rather than being compelled to do so to adhere to regulatory requirements or investor demands. Duel-listing on exchanges such as the American Stock Exchange (AMEX), NASDAQ, and the New York Stock Exchange (NYSE) in the U.S. and the London Stock Exchange (LSE) in the U.K. are proven to be the most beneficial choices (Dodd & Louca, 2012; Ghadhab & Hellara, 2016; Roosenboom & Van Dijk, 2009; Sarkissian & Schill, 2009). Roosenboom and Van Dijk (2009) show that firms who cross-list in either of the two aforementioned markets experience improvements in market valuation. Ghadhab and Hellara (2016) find that U.S. cross-listing leads to greater contributions to price discovery when compared to other foreign exchanges, including the LSE.

Some firms, however, choose to cross-list more regionally. (Dodd, 2013) shows that investors are more inclined to participate in share trading with stocks originating from countries with which they are familiar. Familiarity increases among stocks who exist within a similar vicinity as this has positive effects on the flow of information (Portes & Rey, 2005; Sarkissian & Schill, 2009).

International cross-listing is an extension to traditional services offered by exchanges. This form of financial innovation provides investors with the opportunity to access shares of international firms within the same trading environment they traditionally use. As such, international cross-listing extends the services offered by the exchange by allowing for the easier facilitation of international diversification. International cross-listing also contributes to market completeness for cross-listing firms as it deepens the pool of potential investors. Without access to foreign shares, investors suffer from participating in markets in which they cannot span all states of nature. International cross-listing facilities the movement of funds across an increasing number of states of time and space and allows investors to better manage risk factors through diversification.

Given the current global nature of the financial landscape, firms are choosing to cross-list across exchanges in multiple countries (Ghadhab & Hellara, 2016; Ghadhab & M'rad, 2018). Doing so allows firms to market themselves within an even larger pool of potential investors. The presence of a wider investor pool fuels growth through greater access to funding resulting from improved capital costs (Pagano, Röell, & Zechner, 2002). Therefore, the desire to adapt to increasing globalisation in financial markets motivates the phenomenon of international cross-listing.

In addition to these traditional forms of cross-listing, Multilateral Trading Facilities (MTFs) in Europe have increased international access to shares by allowing for cross-border trading. Academics, however, are unable to determine the exact benefits of such actions with research into the topic leading to equivocal results. Research has deciphered various motivations behind the decision to cross-list.

Consolidation of Investors

Sarkissian and Schill (2009) and Abdallah and Ioannidis (2010) determined that companies cross-list to consolidate the geographically fragmented investor base. By doing so, they bypass the barriers to entry for foreign investments and make their shares more readily available to a wider array of potential investors. Companies that do not cross-list are largely dependent upon the investors in their original listing country. As a result, single-listed companies are unable to benefit from the diversification requirements and risk-sharing of foreign investors. They are also unable to leverage the expertise of informed traders residing outside its sovereign borders and the superior information they may be able to produce (Amira & Muzere, 2011; Bailey, Karolyi, & Salva, 2006; Lee & Valero, 2010). These studies suggest that market completing, globalisation and risk management are influential in the decision to cross-list internationally.

The concept of an investor base fragmented by international borders is one of the most widely studied motivations for the cross-listing of shares. Errunza and Losq (1985) and Alexander, Eun, and Janakiramanan (1987) are among the first studies to model internationally fragmented (also referred to as 'segmented') markets. They find that domestic investors require a lower return on locally listed stocks than they do on securities listed on international exchanges. Errunza and Losq (1985) find that when barriers to entry are not uniform across investor groups, the group which faces greater obstacles when investing incorporates a premium into their pricing model. This premium reduces upon the subsequent cross-listing of the stock. Alexander et al. (1987) find that companies expand upon their investor base and fulfil the investments needs of a more diverse audience when allowed easier access to foreign shares. By expanding the investor base through cross-listing companies also allow for greater risk-sharing among investors which in turn lowers their overall required returns, when compared to singly listed firms. Specifically, foreign investors are less exposed to risks associated with exchange rates, inflation, and interest rates as well as greater financial oversight. Alexander et al. (1987) verify these results empirically and find that non-Canadian stocks which cross-list internationally experienced a decline in required returns compared to when they were singly listed. The result is an increase in the overall share price.

Before 1990, stock markets were found to be greatly fragmented (segmented) across sovereign borders as they did not have access to an internationally diverse array of investors. Empirical studies find that non-US firms experience an increase in share prices upon cross-listing in the U.S. market. Errunza and Losq (1985) and Alexander et al. (1987) show that by listing shares in a foreign market, companies can consolidate their investor base and decrease the level of segmentation in the market (Foerster & Karolyi, 1999; Serra, 1999), leading to an increase in share prices.

However, not all researchers agree that the consolidation of the foreign investor market leads to positive returns. Foerster and Karolyi (1999) find that firms from both developed and developing countries experience similar effects from international cross-listing. This outcome is not intuitive as firms originating from developed markets should have a more internationally consolidated investor base than their developing counterparts. As a result, firms originating from developed markets should not experience the same level of benefits from international cross-listing. In support of Errunza and Losq (1985), Stulz (1999) argues that reducing barriers to entry which significantly limit the investor base should result in a significant decrease in a firm's cost of capital. But the gains recorded in the previous studies are low in comparison to the reduction in the cost of capital (Karolyi, 2006). Stulz (1999) also argues that decreases in barriers to international investment since the 1990s have resulted in the consolidation of foreign investors and the expansion of the investor pool for firms in developed economies. As a result of the increased globalisation of investor pools, cross-listing events should decrease due to their reduced benefits. However, events of cross-listing increased during this period as reported by Karolyi (2006). Therefore, there must exist alternative motivations behind a firm's decision to cross-list.

Improvements to Price Discovery

Expanding the investor pool by consolidating geographically fragmented investors can improve the price discovery process. Permanently compounding high-quality information into the stock price in a timely fashion benefits both the firm and its investors. Price efficiency is important as theoretical modelling shows that stock prices guide managers into making decisions surrounding potential investments (Dow & Gorton, 1997; Subrahmanyam & Titman, 1999).

International cross-listing, particularly in the U.S., can result in improvements to the price discovery process and improves the accuracy of pricing information. These improvements to price discovery provide further evidence that reducing information asymmetry is a supporting factor in the decision to cross-list as doing. In a study of AMEX and NYSE listed shares, Noronha, Sarin, and Saudagaran (1996) find that informed trading increases following international cross-listing, leading to more efficient and informative prices. However, the primary market is still believed to provide the majority of price disseminating information. Foreign exchanges contribute to price discovery as they can often trade shares at prices that differ from those in the primary local exchange. Kaul and Mehrotra (2007) show that Canadian shares cross-listed on U.S. exchanges often trade at noticeably different prices once transactions costs have been accounted for. The U.S. exchanges can be attractive to Canadian investors as they allow them to both save money when transacting as well as open the door to potential arbitrage profits. These results are supported by Gagnon and Karolyi (2010).

Price discovery largely occurs in the primary domestic exchange (Su & Chong, 2007); however, not all studies agree that this is a constant relationship. Using data on U.S.-listed Canadian stocks, Eun and Sabherwal (2003) find that U.S. trading contributes on average 38.1% of the price forming information. The extent of the contribution is proportionally related to U.S. trading volume and inversely related to bid-ask spreads. Pascual, Pascual-Fuster, and Climent (2006) support the notion that contribution to price discovery is related to trading activity. In their study of U.S. cross-listed Spanish stocks, Pascual et al. (2006) find that the Spanish Stock Exchange contributes the vast majority of information due to the high proportional volume of trading activity, compared to the NYSE. Frijns, Gilbert, and Tourani-Rad (2010) study Australian stock cross-listed in New Zealand, and vice versa, from 2002 to 2007. Using the Hasbouck (1995) information share (IS) as well as the Grammig, Melvin, and Schlag (2005) conditional information share, they too find that primary domestic exchange leads in terms of price discovery. However, over time the larger Australian market begins to play a more prominent role in the process for firms of either origin. The contribution of Australian markets is positively related to the growth in the firm and negatively related to its trading costs, as measured by the bid-ask spread. A subsequent study by Frijns, Gilbert, and Tourani-Rad (2015) returns the focus to Canadian firms cross-listed on major U.S. exchanges such as the AMEX, NASDAQ and NYSE. Utilising the Gonzalo and Granger (1995) component share (CS) Frijns et al. (2015) find support for their 2010 study. They conclude that price discovery is positively related to trading activity and negatively to bid-ask spread transaction costs.

Chen, Choi, and Hong (2013) also study U.S. traded Canadian firms. They find that while the U.S. contributes to the price discovery process, it is the local Canadian market, the Toronto Stock Exchange (TSX), which leads in terms of information share. Fernandes and Ferreira (2008)find that the informativeness of stock prices, as measured by stock return variation, improves for firms of developing markets who cross-list in the U.S.. Improved analyst coverage resulting in the discovery and dissemination of new private information drive these improvements as opposed to changes in liquidity, ownership, or adherence to greater accounting standards leads. For this reason, firms from developed economies who cross-list in the U.S. experience negative effects with regards to price informativeness.

Foerster and Karolyi (1999) argue that domestic market improvements to bid-ask spreads for U.S. cross-listed Canadian shares stem from increased competition among U.S. market makers. Moulton and Wei (2009) find the same improvements to transaction costs resulting from international cross-listing; however, they attribute the results to competition associated with the increased availability of substitute investments. Conversely, Noronha et al. (1996) find that spreads do not improve as increased trading by informed investors has adverse effects on the cost of liquidity provision by specialists. As a result, there is not sufficient evidence to imply that a desire to reduce transaction costs for investors motivates events of international cross-listing.

Commitment to Higher Reporting Standards

Companies may choose to cross-list, both internationally and domestically, to signal to investors their intention to adhere to a greater financial reporting standard. This commitment to greater reporting standards leads to improvements in information asymmetry among investors as more information is made publicly available. It also implies a reduction in agency costs as it reduces shareholders' reliance on external monitoring to maintain financial transparency. Theoretical models show that firms prefer to cross-list on exchanges that impose the strictest disclosure requirements. By committing to the most rigorous standard firms improve liquidity and achieve the greatest reductions to their costs of capital (Amira & Muzere, 2011; Chemmanur & Fulghieri, 2006; Huddart, Hughes, & Brunnermeier, 1999) leading to an increase in firm valuation (Bailey et al., 2006; Eaton, Nofsinger, & Weaver, 2007; Roosenboom & Van Dijk, 2009). Liquidity improves as adherence to greater standards allows firms to appeal to a wider range of investors (Fanto & Karmel, 1997). Baker, Nofsinger, and Weaver (2002) use data on foreign firms listed on the NYSE and LSE. They confirm that firms who convey their willingness to adopt stricter financial reporting standards through listing on said exchanges improve their ability to attract new investors. Increased media coverage, as well as greater interest by financial analysts, are partially responsible for the increase in potential investors.

One of the driving forces behind the improvements to liquidity, cost of capital, and firm valuation is the willingness for smaller investors to trade in firms they feel protect their interests (Stulz, 1999). Greater adherence to accounting and reporting standards provides smaller and less knowledgeable investors with the confidence to invest in firms while simultaneously lowering the costs associated with firm monitoring and risk compensation. In return, this allows firms to raise additional investment capital at a more favourable price. By improving capital acquisition costs, the firm can invest in a wider array of potential projects, thus contributing to future growth. Pagano, Randl, Röell, and Zechner (2001) find empirical support for improvements to investor protection surrounding international cross-listing. Along with Reese Jr and Weisbach (2002), Pagano et al. (2001) find that firms who choose to cross-list in the U.S. tend to have weaker investor protection policies in their primary listing country.

There is some contradictory evidence regarding the motivating factors for international cross-listing. Saudagaran and Biddle (1995), Pagano et al. (2001) and Fernandes and Giannetti (2014) find that firms do not tend to cross-list on exchanges that impose more strict accounting requirements. Using data from nine stock exchanges across eight countries from 1981 through 1986, Saudagaran and Biddle (1995) conclude that increased costs associated with foreign listing make firms less likely to cross-list on exchanges with greater disclosure requirements and accounting standards. Pagano et al. (2001) find similar results using data from 1986 to 1997 for European firms cross-listed in the U.S., along with Fernandes and Giannetti (2014) who use data from 1980 to 2006 for foreign firms of 24 countries listed on U.S. exchanges such as the NYSE, AMEX and NASDAQ.

In summary, market completeness, supported by globalisation, contributes to events of international cross-listing. Single-listed companies are unable to benefit from the diversification requirements and risk-sharing of foreign investors. They are also unable to leverage the expertise of informed traders residing outside its sovereign borders and the superior information they may be able to produce (Amira & Muzere, 2011; Bailey et al., 2006; Lee & Valero, 2010). This commitment to greater reporting standards leads to improvements in information asymmetry among investors as more information is made publicly available. It also implies a reduction in agency costs as it reduces shareholders' reliance on external monitoring to maintain financial transparency (see Figure 2-8).

2.3.3 High-Frequency Traders

The ability of computer programs to source liquidity as well as identify liquidity gaps across numerous exchanges simultaneously has also aided in the consolidation[6] of equity markets. Recent technological advancements have resulted in the creation of a new investor class that can process information, execute trades, and submit and cancel order book quotes at high speeds. Algorithmic traders (AT) and their more controversial subgroup, high-frequency traders (HFT), have recently entered markets and now regularly interact with the more traditional, slower group of investors. Orders submitted by this new investor class are submitted automatically by advanced computing algorithms, rather than through traditional means. AT and HFT orders distinguish themselves from traditional trades by their fast reaction times, short holding periods, and frequent trade and order book activity resulting in significant increases in trading volume and order book adjustment, respectively. Firms that employ HFT strategies are therefore able to reduce search costs. They can process the states of several markets, both domestic and international, at speeds that far exceed those which can be achieved exclusively through human intervention. This innovation extends upon existing trading strategies by providing firms with an alternative method with which to access

[6] The reverse of market fragmentation.

liquidity. Firms can adopt these new techniques and change the process by which they transact or continue to use traditional means to buy and sell shares.

Previously, markets were fragmented in that they would only allow for participation by local investors. Today, however, liquidity can be sourced by local and well as international investors, with or without the aid of tools to improve latency. This section reviews research into whether the fragmentation of investors into various subclasses benefits markets. It also discusses whether decisions should be made to isolate such investor groups from traditional investors, that is, to fragment the market, to improve market conditions. In recent years exchanges have discussed and even implemented policies that exclude certain high-frequency trading (HFT) activities under the guise of investor protection[7]. This results in the fragmenting of the market into trading pools that differ based on their level of non-human intervention. For example, 1 April 2012 saw the Investment Regulatory Organisation of Canada introduce a limit on the number of electronic messages submitted by market participants resulting in a decrease in message traffic of roughly 76%. Exchanges and regulators argue such actions are warranted when certain investor classes negatively impact markets through increased adverse selection and systematic risk as well as the saturating markets with predatory and non-viable liquidity (Biais & Foucault, 2014).

The inclusion, or consolidation, of algorithmic and high-frequency traders into the investor pool is said to come with several benefits and risks. According to the policies outlined in the second iteration of the Markets in Financial Instruments Directive (MiFID II), some of the key benefits of software-assisted trading includes greater order execution, increased liquidity through greater investor consolidation, narrower bid-ask spreads and decreases in short-term volatility leading to more efficient pricing. Therefore, in addition to benefiting from the improved search capabilities, HFTs are motivated by their ability to reduce transaction costs.

However, MIFID II policymakers outline that consequences arising from the inclusion of such an investor class include the submission of duplicate or predatory orders, increased order book noise, and overreaction to information.[8] Predatory actions such as quote stuffing, where thousands of quotes are generated and submitted every second to increase market latency, are found to harm liquidity (M. Ye, Yao, & Gai, 2013). The Securities and Exchange Commission (SEC) also acknowledges that HFTs are a potential source of 'phantom

[7] Aquis exchanges has banned predatory HFTs in order to protect investor liquidity (Source: https://www.aquis.eu/trade-aquis-ban-predatory-hfts/)

[8] The Flash Crash is one of the most famous overreactions resulting from HFT. It occurred on the Dow Jones Index in May of 2010.

liquidity'. Phantom Liquidity consists of orders submitted order books that subsequently disappears when they are most needed by long-term investors.

Theory of HFT

While those who employ HFT strategies often benefit from their decision, theoretical modelling implies that increased HFT activity has adverse effects on market conditions. Evidence suggesting that HFT strategies are motivated by the desire to improve pricing information and reducing information asymmetries is mixed, at best (Cartea & Penalva, 2012). Their own self-interest instead motivates them. Investor welfare deteriorates through greater information inefficiency and volatility. High frequency trading models show that profits resulting from engaging in such practices largely come at the expense of traditional investors who are slower in their responses to changes in market conditions.

HFTs are not known to be sources of new information (Chaboud, Chiquoine, Hjalmarsson, & Vega, 2014). Instead, they facilitate the process of incorporating new information from sophisticated investors through the observations order flow, volume, and price signals (Biais & Foucault, 2014; Foucault, Hombert, & Roşu, 2016). By taking advantage of their speed, HFTs can piggyback on the costly information gathering of other investors for profit. Such actions negatively impact the informativeness of prices as HFT free-riding dis-incentivise investors from acquiring information that can contribute to price discovery (Grossman & Stiglitz, 1980). Foucault et al. (2016) conclude that increased HFT activity leads to an emphasis on short-lived and imminent information. As a result, the prominence of trades involving long-term information decreases leading to an impairment in the price discovery process. In this situation, market-makers experience greater adverse selection risk leading to a reduction in liquidity. Emphasis on reaction speed can also create more noise leading to a deterioration in the efficiency of prices. Jarrow and Protter (2012) also find that HFT can create temporary deviations from fundamental values leading to less efficient prices.

In their model, which includes HFTs operating alongside liquidity traders and market makers, Cartea and Penalva (2012) find that HFT activity adversely affects liquidity traders. While trading volume increases within the market, liquidity traders suffer from exposure to greater volatility and price impacts. Market makers are less affected as any losses to market shares from HFT competition are compensated for by greater profits.

Biais and Foucault (2014) find that slower investors experience severe adverse selection when competing with faster investors who can more quickly process and react to information. This can potentially discourage retail investors and smaller firms from participating in markets as trading costs increase and high price impacts due to market illiquidity become more frequent. It can also encourage investment by larger firms into technologies to improve reaction speeds to maintain competitiveness rather than information gathering, which contributes to price efficiency. The fragmentation, that is, exclusion or isolation, of HFT investors can, however, negatively impact other market participants. HFTs increase the likelihood of trade execution due to their innate ability to quickly source and provide liquidity across different exchanges, thereby consolidating liquidity across several trading venues.

Menkveld and Jovanovic (2016) find a similar adverse selection cost in their model. They find that HFTs can introduce adverse selection into the market when such risks are inherently low or non-existent. A fragmented market in which HFTs were excluded from such exchanges, allowing for buyers and sellers to interact in the limit order book, would be more beneficial to investors. However, if adverse selection risks were already present, HFTs who benefit from avoiding such risks could impart some of the benefits to investors, thereby improving market liquidity and lower transaction costs.

Empirical HFT Research

Empirical results generally concur with the existing models regarding greater adverse selection risk resulting from increases in HFT activity. Brogaard, Hendershott, and Riordan (2014), Brogaard, Hendershott, and Riordan (2017), and Carrion (2013) and all use a similar NASDAQ data-set which explicitly identifies HFTs and find that their participation results in increased adverse selection costs for other market participants. This dataset contains information on trades in 120 stocks by 26 firms that identify themselves as HFTs from 2008 to 2009. They conclude that the liquidity benefits are not purely one-sided in that they both supply and consume liquidity. Brogaard et al. (2014) also find that HFTs convey information through the use of market orders. They buy market orders prior to positive changes in market prices resulting in permanent price effects that exceed those of traditional, non-electronic investors. Chaboud et al. (2014) contradict these findings using foreign exchanges market data and claim that human trades are more influential on prices and convey more information than those originating from algorithms.

However, the previous empirical studies suffer in that the scope of their dataset, and the overall impact of HFT, is severely limited. By only using markets where HFT activities are explicitly identifiable, they do not gain clear insight into the market-wide impacts of HFT.

Equity markets have grown increasingly fragmented and HFTs often participate simultaneously in multiple exchanges. When studies cannot explicitly identify HFT activities, they instead choose to investigate the changes in market conditions surrounding key changes to market structure. They must also resort to using proxies for the levels of algorithmic of high-frequency trading. While this allows researchers to study more geographically diverse data, it comes at a cost. Certain proxies may not accurately measure exclusively high-frequency activity and include noise from low-speed activities.

Several studies investigate changes to the market such as technological enhancements used to improve market latency. Hendershott, Jones, and Menkveld (2011) study the impact of the inclusion of automated quote dissemination (Auto-quote) on the NYSE which improved the efficacy of algorithmic trading. Using data on 1,082 listed stocks from December 2002 to July 2003, Hendershott et al. (2011) find the effects automated quote dissemination to be beneficial. They use the number of electronic messages, which they normalise by trading volume, as a proxy for algorithmic trading. Particularly for large stocks, algorithmic trading (AT) results in narrower quoted and effective spreads and decreases adverse selection costs, fuelling improvements in liquidity. It also shifts the dynamic of price discovery and sees order books quotes increasingly becoming the source of permanent price forming information when compared to transaction prices. Effects on smaller sized firms are not found to be statistically significant.

In contrast, McInish and Upson (2013) show that slow traders suffer from adverse prices when interacting with HFTs who benefit from lower latency. Fast traders intentionally avoid certain orders leaving slower traders to fulfil them at less favourable prices. The results in McInish and Upson (2013) support earlier assertions that HFTs are motivated by self-interest and are not necessarily interested in improving market conditions.

Hendershott and Riordan (2013) study data on 30 DAX stocks trading on the Deutsche Boerse in January 2008. They find that ATs play a greater role in monitoring liquidity and identifying occurrences of mispricing compared traditional investors. When it is inexpensive to do so, that is, when bid-ask spreads are narrow, ATs consume liquidity. Conversely, they choose to supply liquidity when transaction costs increase, and bid-ask spreads are wide. Submitting more efficient quotes and demanding liquidity to move prices when it is favourable to do so implies that ATs contribute to price efficiency leading to more stable market conditions. A subsequent study by Brogaard et al. (2014) confirms that HFTs play an imperative role in the price discovery process. However, this is merely a by-product of HFT strategies rather than their intention.

Using data from 42 equity markets across 39 countries from 2001 to 2011, Boehmer, Fong, and Wu (2015) find that AT generally improves liquidity and leads to narrower bid-ask spreads. Like in Hendershott et al. (2011), they find that benefits are substantial for firms with a higher market capitalisation. However, unlike Hendershott et al. (2011), Boehmer, Fong, and Wu (2015) find support for the negative liquidity implications of AT on smaller firms. E. Boehmer, Fong, and Wu (2013) propose that AT also leads to improvements in the efficiency in which price forming information in compounded into the price. Using autocorrelation of stock returns as a measure of price inefficiency they find a negative relationship when they, similar to Hendershott et al. (2011), use the normalised number of messages as a proxy for AT. Unfortunately, any improvements come at the cost of increased volatility.

Joel Hasbrouck and Saar (2013) use NASDAQ order-level data from 2007 to 2008. They identify HFT activity by the cancellation and immediate (within one second) resubmission of limit orders. Activities occurring at such speeds are unlikely to originate from traditional investor classes. Using the level of cancel-and-replace activity as an instrumental variable, Joel Hasbrouck and Saar (2013) conclude that increases in HFT activity improve market quality. They observe that increases in the level of cancel-and-replace activities correspond with a reduction of spreads and short-term volatility as well as an increase displayed depth. However, Joel Hasbrouck (2018) finds that high frequency quoting can lead to increases in the short-term volatility of spreads that exceed those implied by long-term fundamentals.

Hagströmer and Nordén (2013) use member-level data for 30 stocks based on the NASDAQ-OMX Stockholm exchange from 2011 to 2012. They classify firms into HFT, non-HFT, and hybrid groups to construct an accurate HFT dataset. They find support for HFTs and argue that HFTs do indeed reduce short-term volatility, as documented in MiFID II. Hagströmer and Nordén (2013) also identify opportunistic HFTs by their low message-to-trade ratios and higher investor holdings. Market-making HFTs exhibit reverse characteristics (high message-to-trade ratios and low inventory levels) and contribute to the majority of trading volume.

High-frequency methods which allow for the continuous updating of order books through frequent order submissions and cancellations can negatively impact liquidity. Markets experience widening spreads (Han, Khapko, & Kyle, 2014)and a decline in depth which is particularly detrimental to traditional investors Budish, Cramton, and Shim (2014). Upson and Van Ness (2017) also show that depth is adversely affected by AT at the national best bid and offer price. Hasbrouck (2018) also finds that high frequency quoting can lead to increases in the short-term volatility of spreads that exceed those implied by long-term fundamentals.

Egginton, Van Ness, and Van Ness (2016) identify increased HFT activity by periods of abnormally frequent quote submission. They use periods during which quoting activity exceeds 20 standard deviations above standard levels for a particular stock over one to ten-minute periods. They find that these events are common and can occur hundreds of times per day across a wide array of stocks. During these times, they find that markets quality suffers in that bid-ask spreads widen and price volatility increases.

In summary, the innovation of HFT is an extension to existing trading methods. Reductions in transaction and search costs motivate HFT. HFTs can process the states of several markets, both domestic and international, at speeds that far exceed those which can be achieved exclusively through human intervention. This innovation extends upon existing trading strategies by providing firms with an alternative method with which to access liquidity. The desire to capitalise on recent technological advancements also motivates innovation in HFT (see Figure 2-8).

2.4 Substitutionary Fragmentation

Substitutionary fragmentation occurs upon the introduction of an alternative asset alongside existing financial assets. These events fragment the market as they divert investment to new products and limit the amount of trading in any given asset. Alternative assets can take the form of derivative products as well as variants of existing offerings. Options markets are used as a means of studying the fragmentation of investors upon the introduction of substitute investment products. This section explores what motivates investors to enter such markets and the extent to which such innovations affect conditions in traditional equity exchanges. Next, this section explores substitute cryptocurrencies and the motivating factors behind their development. Finally, it addresses the impact that these alternatives to Bitcoin have on the overall cryptocurrency market. The driving factors behind substitutionary fragmentation are summarised in Figure 2-9 below.

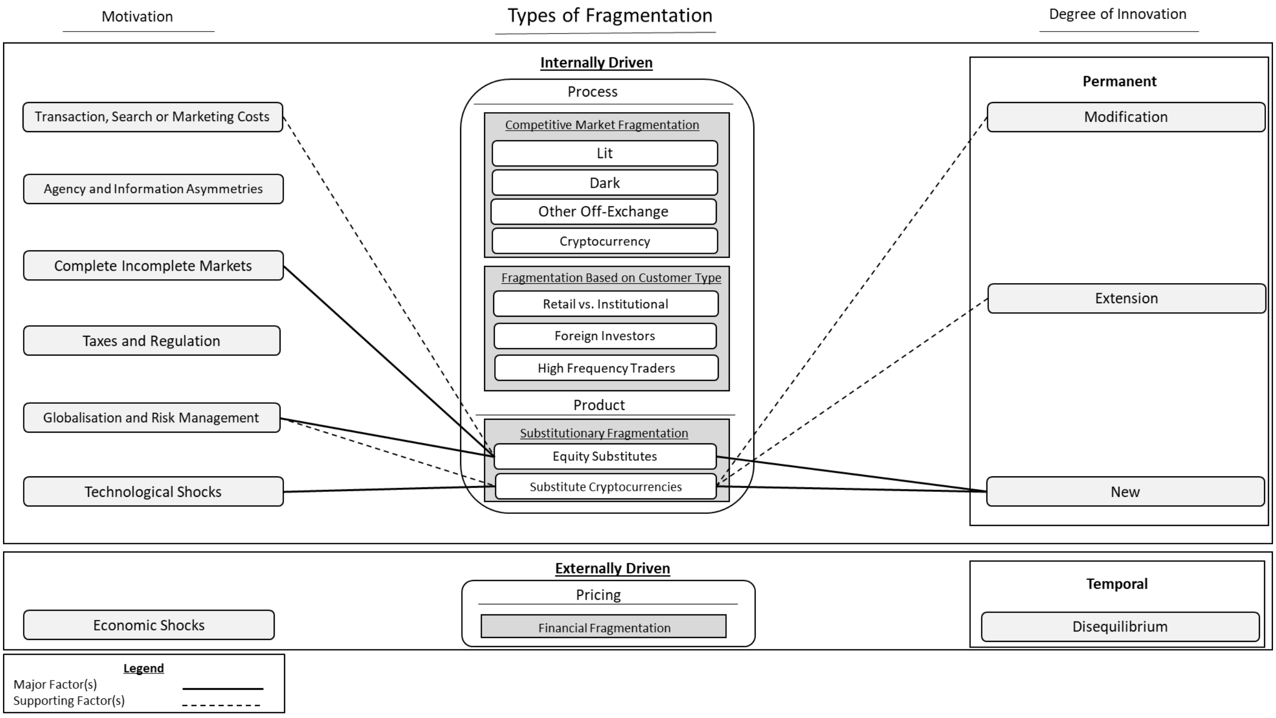

Figure 2-9: Taxonomy of Market Fragmentation (Substitutionary Fragmentation)

The taxonomy in Figure 2-9 depicts the factors that motivate the fragmentation of investors across financial assets through the introduction of substitute financial assets. Substitutionary fragmentation normally leads to the formation of new products and services. Equity substitutes, such as equity-based derivatives, fragment investors by introducing new asset classes. Equity substitutes promote market completeness as they allow investors to engage new strategies that mitigate risk. A secondary motivator is improved transaction costs. Increased informed investor activity also reduces levels of information asymmetry, but this is more a consequence of derivative (option) trading rather than the motivation behind such innovations. In contrast, technological advancements in computing and decentralised networking are the primary motivators leading to the development of modern-day cryptocurrencies such as Bitcoin as currency substitutes. The subsequent development of altcoins represents a modification or extension upon existing features offered by Bitcoin. A desire to mitigate risk associated with traditional fiat currencies and monetary policies also motivate the development and adoption of new cryptocurrencies. This implies that globalisation and risk management plays a significant role in the growing popularity of cryptocurrencies (see Figure 2-9).

2.4.1 Options

Options markets are the primary example of substitutionary fragmentation in equity. The creation of equity options offers investors an alternative to traditional forms of equity investment, though they are also used in conjunction with share purchases. Derivatives, including options, futures, and swaps, provide investors with several benefits. For one, they allow investors to engage in strategies that may otherwise not be available with traditional asset classes such as equity shares. Therefore, options promote market completeness. Options can help reduce the cost of portfolio diversification. They also allow investors to leverage their investment funds better to take on positions that would otherwise be too expensive. The cost of short-selling proves restrictive, as in some cases, participants are required to provide collateral. For example, in the United States (U.S.), Regulation T as outlined by the Federal Reserve Board requires an initial margin of 150% of the value of the short sale. This means that even after investors locate a counterparty willing to lend them their shares they are still responsible for contributing 50% of the value of the share sale towards the initial margin in addition to providing the lender with compensation. Finally, options also allow investors to mitigate risk associated with an investment in equity shares.

The relationship between options and their ability to contribute to the development of complete markets is a key motivating factor behind the development of these and other derivative products. The relationship between options and short-sale constraints is used to study innovations that lead to substitutionary fragmentation. Short-sale constraints take the form of both costs and risk associated with short-selling as well as legal restrictions imposed on investors. Damodaran and Lim (1992) and Figlewski and Webb (1993) find that short-selling activity increases upon the introduction of options. Their research shows that if retail investors are subject to greater short-selling constraints compared to options market makers, then short-selling activity in the market increases. Increased short-selling activity occurs as retail investors look towards options markets to employ strategies that mimic short-sales. These actions fragment the market as traditional equity investors are forced to migrate to derivative markets to employ their desired investment strategies. By synthesising short equity positions, options help complete the market for retail investors who wish to engage in bearish investment strategies. However, this increases the overall number of short positions as market makers, who face lesser short-selling constraints, use short-selling as a means of hedging positions taken by options traders.

Negative abnormal returns are also found to convey the notion that options help complete markets by reducing short-sale constraints. Miller (1997) claims that impediments to short-selling discourage bearish investors from participating in the market. As a result, investors with a more positive outlook on future expectations play a greater role in formulating prices. Therefore, by allowing investors to circumvent short-sale restrictions, greater use of options is associated with negative abnormal returns as prices adjust to account for the views of more pessimistic investors. Sorescu (2000) and Danielsen and Sorescu (2001) find empirical evidence to support Miller's (1977) findings when studying listed options from 1980 to 1995. Faff and Hillier (2005) find contradictory results using data on U.K. options. However, Faff and Hillier (2005) focus exclusively on returns corresponding to the options first trading day. Therefore, an influx of informed trading arguably drives the results. This occurs as investors use options to leverage their positions better, thereby taking advantage of the improvements to transaction costs that options provide. Chakravarty, Gulen, and Mayhew (2004) also find that the level of price discovery associated with options is higher for out-of-the-money options. The increased informativeness of out-of-the-money options provides further support that options traders value leverage as a means of reducing costs. Increased informed investor activity reduces levels of information asymmetry and provides support for the efficient market hypothesis. However, this is a consequence of options trading rather than the motivation behind such innovation and the resulting increase in its popularity.

Improvements to market efficiency are not considered a leading motivational factor behind this form of substitutionary fragmentation, though they play a supporting role. Fedenia and Grammatikos (1992) find that bid-ask spreads reduce upon the introduction of options to the market. Lower bid-ask spreads improve market conditions by reducing transaction costs. Options are also found to contribute to maintaining efficient price levels in equity markets (Chakravarty et al., 2004; Patel, Putniņš, Michayluk, & Foley, 2018). Chakravarty et al. (2004) study 60 U.S. firms from 1988 to 1992 using a variation of Hasbrouck's (1995) information share (IS). Their goal is to measure the level to which options contain permanent price adjusting information regarding stock prices. They find that options markets contribute roughly 17% to the price discovery process. Patel et al. (2018) find similar results in their study of U.S. stocks and exchange trades funds (ETFs). Using another variation of the IS measure, the information leadership share, they find that options markets contribute roughly 33.2% of all price adjusting information.

Finally, risk mitigation is a potential motivational factor behind the innovation of options, which is a form of substitutionary fragmentation. Options trading is synonymous with hedging and often employed by institutional investors as a means of protecting their investments. C. W. Smith and Stulz (1985) support the concept that firms see risk aversion as a motivating factor behind their hedging practices. Fehrs and Mendenhall (1994) investigate the level of institutional investment in stocks with traded options compared to those without traded options. They find that stocks with options have a greater proportion of institutional investment in their shares. Schizer (2000) shows that tax incentives associated with employee stock option plans do not motivate in institutional investors participate in options trading. This is due to the existence of noticeable tax disadvantages to hedging restricted stocks.

In summary, the creation of equity substitutes, that is, equity-based derivatives, fragments investors by introducing new asset classes. Equity substitutes promote market completeness as they allow investors to engage in strategies that may otherwise not be available through traditional means. Allow investors to mitigate risk associated with an investment in equity shares also promotes innovation leading to the introduction of substitutes products. Equity substitutes lead to improvements in transaction costs. Increased informed investor activity reduces levels of information asymmetry and provides support for the efficient market hypothesis. However, any reduction in information asymmetry is a consequence of options trading rather than the motivation behind such innovations (see Figure 2-9).

2.4.2 Substitute Cryptocurrencies

Since its launch in 2009, Bitcoin is considered the oldest and most popular of the modern-day cryptocurrencies. Its formation stems from a 2008 paper by an anonymous person or group working under the name Satoshi Nakamoto which outlines the structure of the currency. Today, Bitcoin and other cryptocurrencies are viewed as a medium of exchange and also as an alternative investment for speculative investors (Baur & Dimpfl, 2019; Yermack, 2015). With average quoted and effective spreads below those available in equity markets, cryptocurrencies are supportive of retail investor trading activity (Dyhrberg et al., 2018).

Bitcoin's key innovation includes being the first completely decentralised and distributed currency. It operates without the need for either a third-party to manage its value, supply, facilitate and clear transactions, or maintain a record of client accounts. Therefore, Bitcoin represents an entirely new innovation in the world of financial assets. Other forms of virtual currencies have existed in the past. However, recent technological advancements in computing and decentralised networking proved to be catalysts in the development of modern-day cryptocurrencies. Without improvements to computing speeds and device connectivity, cryptocurrencies would only exist in theory, especially at the scale in which they currently operate.

Political Discontent

Political discontent and mistrust of the role government and large financial institutions play in monetary policy are among the most wildly studied aspects surrounding the growth of cryptocurrencies. A 2014 survey finds that nearly 60% of Bitcoin users identified as having libertarian values (Lustig & Nardi, 2015). Libertarians promote, among other things, the importance of individual freedom, privacy, and disbelief in the ability for authoritative powers to effectively manage economic policy. These views are not only shared among the users of cryptocurrency but are common with the founders as well. Nakamoto (2019) states that a fundamental problem with traditional currencies is the level of trust that society must place in traditional financial institutions such as banks, noting that they have breached this trust numerous times. The desire to mitigate risk associated with traditional fiat currencies and monetary policies, due to their distrust of traditional financial institutions, motivate Bitcoin developers and its users. By not being subject to such policies, Bitcoin and other cryptocurrencies have succeeded in developing a globalised currency platform that spans sovereign borders.

Altcoins

However, Bitcoin is not the only modern cryptocurrency. The cryptocurrency market soon fragmented and presented investors with a plethora of alternative currencies, otherwise referred to as altcoins. This is due to the source code for Bitcoin is readily available online[9], thus acting as a catalyst for growth by lowering barriers to entry for new currency founders. Beginning in 2011, developers adopted this readily available resource and introduced new currencies into the market that either slightly or widely vary from the original offering. Some have opted to copy the original code and make only slight variations to distinguish themselves from Bitcoin. As a result, many cryptocurrencies differ very little from each other (Kogias et al., 2016), and the market views new cryptocurrencies as direct substitutes from a technical standpoint. However, other cryptocurrencies have brought forth and incorporated significant advancements. Therefore, subsequent entries into the cryptocurrency market are view as

[9] A current version of the Bitcoin source code can be found on GitHub. (https://github.com/bitcoin/bitcoin)

either modification or extensions to existing offerings. The degree of innovation is dependent on the level of differentiation between the new cryptocurrencies and existing ones.

Litecoin and Peercoin are among two early Bitcoin competitors. Categorised as alternatives that improve upon the shortcomings of Bitcoin, they offer improved transaction times and improved or non-predefined coin limits. Litecoin and Peercoin also reduce the reliance on specialised mining hardware, which poses a threat to the ultimate goal of a network decentralisation. Specialised hardware empowers only the most technologically advanced miners as it encourages miners to work together by merging into larger pools. Litecoin and Peercoin are two examples are instances of modifications to the original product. Dowd and Hutchinson (2015) argue that the potential for miners to collude and amass a minimum 51% market share may eventually lead to the collapse of Bitcoin. The subsequent introduction of services such as CoinCreator.net further facilitated the diversity in cryptocurrencies by allowing individuals with no programming experience to create new currencies.

According to Tarasiewicz and Newman (2015), there were ten competitors to Bitcoin in circulation by the end of 2011. The oldest and most widely known of these altcoins in Litecoin. Litecoin was established in 2011 and improved upon Bitcoin by upgrading the confirmation speed of transactions by 75%. The number of Bitcoin alternatives increased to 215 by the end of 2013, with only a small minority of 5 cryptocurrencies operating without the use of the publicly available Bitcoin source code. Today, there are 2,136 cryptocurrencies on offer to investors, according to CoinMarketCap.com. Of these 2,136 cryptocurrencies, only 12 have a market capitalisation of at least $1 billion. Ease of implementation, as well as the level of profitability new cryptocurrencies present to their founders, represent key motivational factors behind the increase in the number of cryptocurrencies (Gandal & Halaburda, 2016). Bitcoin, however, remains the dominant cryptocurrency with a market capitalisation of approximately 50% as of March 2019 (Figure 2-10)[10]. Velde (2013) argues that due to its first-mover advantage, Bitcoin has solidified itself as having a ‘quasi-monopoly’. However, Bitcoin's dominance is under threat from the ever-competitive landscape resulting from the introduction of new altcoins.

[10] Source: Coinmarketcap.com

Figure 2-10: Market Capitalisation of Cryptocurrencies

Source: Coinmarketcap.com (March 2019)

The current number of active cryptocurrencies does not, however, fully represent the level of activity in the market regarding new entrants. While many new cryptocurrencies have entered the market since the introduction of Bitcoin, many have not managed to survive. Lánský (2016) finds that of the 1278 cryptocurrencies identified in their study, more than half (688) no longer exist. Of those 688 now-defunct currencies, 399 ceased operations within their first 24 weeks. If a currency manages to survive for 124 weeks, the probability of failure reduces significantly, with only three cryptocurrencies failing beyond this point. These figures convey the competitiveness of the cryptocurrency market.

Lánský (2016) finds that competition from more innovative currencies is a driving factor leading towards significant currency devaluation of at least 10%. A consequence of this is the potential failure of a cryptocurrency. Lánský (2016) also identifies the 2013-2014 pricing bubble and failure of national cryptocurrencies as leading factors in significant currency devaluation. Regarding the regulation of the creation of new private currencies, Williamson (2002) presents a matching model that allows for the circulation of private money. They find that, despite problems associated with coordination and private information, private currencies are superior to fiat ones in that they allow for the intermediation of investment. As a result, Williamson (2002) argues that restrictions on the issue of private currencies are not in the best interest of the market.

Therefore, Bitcoin, altcoins, and other private currencies represent permanent innovation. The degree to which they differ from each other determines the degree of innovation they propose. Truly novel offerings, particular first-movers such as Bitcoin, are new innovations. Others build upon existing offerings through extension or modification. Cryptocurrencies take advantage of technological shocks to distinguish themselves from other asset classes and each other to gain market share.

Modelling Competition

The study of competition amongst private currencies has a long history. Hayek (1990) laid the foundation for modern works on the denationalisation of currencies and their ability to compete. Hayek (1990) argues that governments hold a monopoly on currencies at the detriment to society as individuals must continue using the currencies available despite any flaws they present. Hayek (1990) argues that an economy in which financial agencies can independently issue new currencies has a positive effect on all available currencies, including the previously monopolistic national currency. These positive effects occur as the failure to conform to the best standard available leads to the failure of any substandard currencies. Proof of Hayek's (1990) theory is evident today as only a handful of cryptocurrencies maintain significant market shares. Other, more inferior, currencies fail due to their non-competitive offerings.

Hayek (1990) argues that there exists an equilibrium price level among competing private currencies. However, most subsequent studies argue that such an equilibrium does not exist. Calvo (1978) and White (1999) propose that this is due to a time-consistency problem where issuers of a private currency believe that they will eventually limit the issuance but fail actually to do so. Taub (1985) provides proof supporting the lack of equilibrium using an overlapping-generations model.

Fernández-Villaverde and Sanches (2017) present the first modern theoretical study into competition among privately issued currencies. Their model uses the standard (Lagos & Wright, 2005) approach while adding a feature whereby entrepreneurs create on currencies to maximise profits better. The study differentiates itself from previous works by not allowing currencies to be redeemed for other assets. In contrast to previous studies, Fernández-Villaverde and Sanches (2017) find that there exists an equilibrium where the prices of competing currencies stabilise. They also find that, like government-issued currencies, private currencies are susceptible to devaluation due to inflationary effects. Inflationary effects have the power to reduce the value of each currency to zero over time (Obstfeld & Rogoff, 1983). Lagos and Wright (2005) show that in a world with only private currencies, it is not possible to achieve an optimal money supply in the way that is possible with the supply of goods and services. They also find support for the notion that a single private currency can dominate all others and become the lone source of currency in the market, thereby reducing the level of substitutionary fragmentation. Competition plays a vital role in determining whether the development of new currencies represents a permanent change to the investment landscape. Failure to compete leads some cryptocurrencies to only exist in a temporal sense.

Price Dynamics

Other research into competing cryptocurrencies focuses on pricing dynamics and attempts to identify the mechanisms behind changes in the value of various cryptocurrencies. Gandal and Halaburda (2016) study the change in prices for seven cryptocurrencies from May 2013 to July 2014 on the Btce exchange, which at the time represented a 30% of cryptocurrency exchange activity (Gandal & Halaburda, 2016).They focus on Bitcoin (BTC) and Litecoin (LTC) which at the time of the study, represent market shares of 90% and 5%, respectively. The remaining five currencies, each of which represent less than 1% of the total market share of cryptocurrencies as of January 13 2014, are Namecoin (NMC), Feathercoin (FTC), Novacoin (NVC) and Terracoin (TRC). The study aims to explain price variations as either being caused by a 'reinforcement effect' or 'substitution effect'. The reinforcement effect argues that the popularity of a currency drives its future growth as investors gravitate towards a single currency believing that it will eventually dominate all others in the market. The substitution effect attributes price changes to investors migrating to new currencies. Investors migrate to currencies that either innovate upon existing offerings or are viewed as being overvalued or too volatile. Gandal and Halaburda (2016) find that neither effect is dominant in the early stages of the study. However, starting in October 2013, the authors find that the substitution effect reveals itself as a key explanatory factor in the synchronous changes in pricing among the cryptocurrencies included in the study. However, Gandal and Halaburda (2016) acknowledge that some of the increases in the substitutional effect are due to the rising popularity of the cryptocurrency market. The reinforcement plays a more significant role in price changes in the final period of the study. During this time, the price of Bitcoin increased while the remaining cryptocurrencies experienced devaluation. Such price patterns are indicative of migration of investment towards the dominant currency.

Corbet, Lucey, Peat, and Vigne (2018) further investigate the informational linkages between cryptocurrencies and measurements of investable assets. The key measures they employ are market indices, gold prices, and the USD exchange rate. Using a variance decomposition introduced by Diebold and Yilmaz (2012), Corbet et al. (2018) measure the direction and intensity of informational spillovers across assets. They do not find a strong relationship between cryptocurrency prices and those of other asset markets. However, they do find that Bitcoin prices have a significant effect on both Litecoin and Ripple prices with spillovers of 42.3% and 28.37%, respectively. Conversely, spillover from Litecoin and Ripple onto Bitcoin prices is minimal, at 5.47% and 7.11%, respectively. These results position Bitcoin as a clear leader in cryptocurrency pricing.

In summary, Bitcoin represents an entirely new innovation in the world of financial assets. The subsequent development of altcoins represents a modification or extension upon existing features offered by Bitcoin. This is because most altcoins rely on publicly available Bitcoin source code for their foundation. Recent technological advancements in computing and decentralised networking act as the motivating factor leading to the development of modern-day cryptocurrencies. A desire to mitigate risk associated with traditional fiat currencies and monetary policies also motivate the development and adoption of new cryptocurrencies. This implies that globalisation and risk management plays a significant role in the growing popularity of cryptocurrencies (see Figure 2-9).

2.5 Financial Fragmentation

Financial fragmentation is defined as the lack of perfect market integration. Under such conditions, the law of one price no longer holds and markets move towards a state of disequilibrium. Instances of financial fragmentation are most common in debt markets. For example, they occur when yield spreads on bonds from various countries differ once all relevant risk factors are accounted for (Baele, Ferrando, Hördahl, Krylova, & Monnet, 2004). Unlike previously discussed forms of fragmentation, financial fragmentation is not internally motivated by the goals of market participants (see Figure 2-11). Financial fragmentation does not result from the explicit actions of individuals or firms who aim to change how investors transact in financial markets through the modification of processes and products. Rather, external shocks lead to financial fragmentation. Financial fragmentation is a consequence these external shocks, rather than the cause. Therefore, since financial fragmentation does not fall under the traditional 'process' and 'product' categories of innovation, 'pricing' is proposed as a new classification (see Figure 2-11).

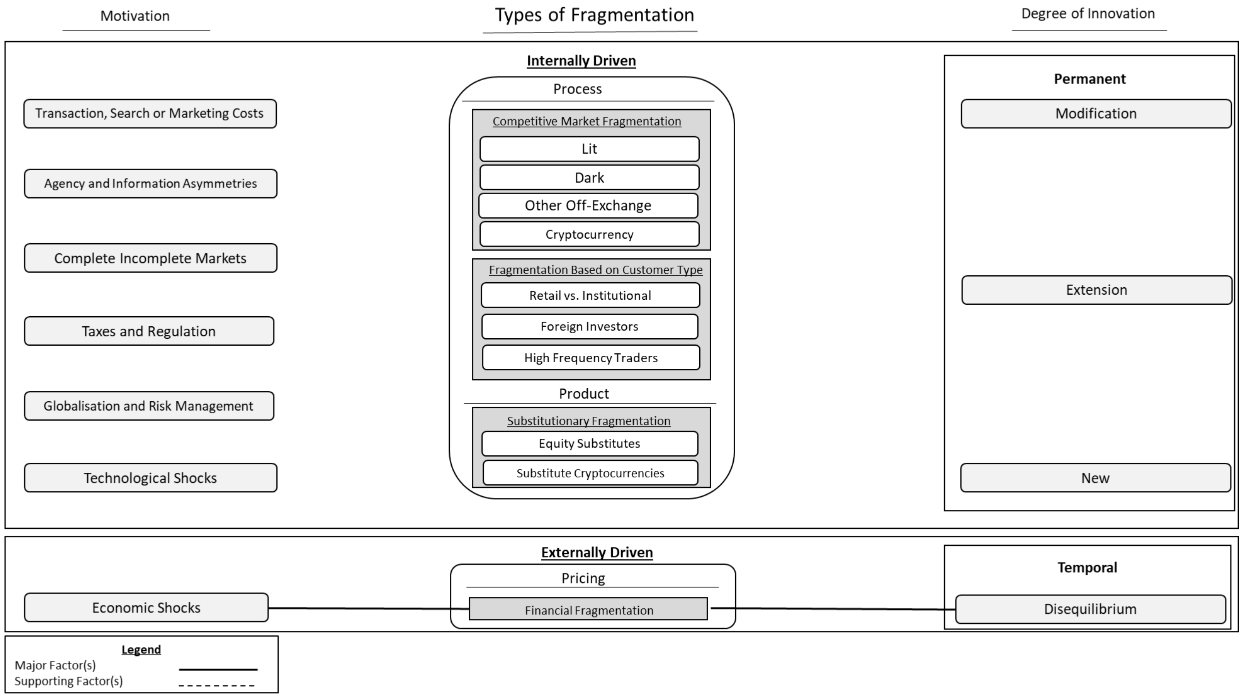

Figure 2-11: Taxonomy of Market Fragmentation (Financial Fragmentation)

Existing studies agree that levels of heterogeneity in bond yields are not sufficient as a sole indicator of market fragmentation (Zaghini, 2016). Heterogeneity in bond yields is not sufficient because spreads are affected by the issuer's credit rating as well as the various features of a bond, including its liquidity and duration. Therefore, the first step in determining the extent of financial fragmentation is controlling for the potential risk factors that influence the premium. After accounting for all risk factors, any deviations are attributed to country-specific and signify the presence of cross-border financial fragmentation (Zaghini, 2016). This section focusses on instances of financial fragmentation in Europe. Europe has experienced multiple changes in levels of financial fragmentation over the past two decades, as is used as a backdrop for the majority of research in the field (Baele et al., 2004; de Sola Perea & Van Nieuwenhuyze, 2014).

Since integration efforts began in the 1990s, the Eurozone has experienced significant market integration and has benefited through increased trade and capital flows across its member states (Baele et al., 2004). These effects were exacerbated in 1999 upon the introduction of the Euro currency as it eliminated any exposure to Euro-wide exchange rate risk for its members. The formation of the Eurozone and adoption of the Euro currency represents two significant economic shocks that motivated changes in the levels of financial fragmentation in

Europe. From the introduction of the Euro currency until 2007, the Eurozone experienced rapid financial integration evident in terms of both the volume and prices of fixed income (de Sola Perea & Van Nieuwenhuyze, 2014).

However, integration of Eurozone credit markets began to subside in 2007 upon the beginning of the subprime crisis. Most notably, it was after the collapse of Lehman Brothers in 2008 that European financial markets began to experience great duress, which revealed itself in the form of a freeze within the interbank market, increased reliance on ECB liquidity facilities, and greater deviation in sovereign debt yields. Bank lending rates also began to differ across national borders, and retail investors began to favour domestic securities over foreign securities. Battistini et al. (2014) refer to the return to domestic securities by investors as a fragmentation event of European credit markets. As a result, globalisation and market completeness suffered due to investors' desires to isolate themselves into domestic investment pools.

The fragmenting events continued into 2010, where government intervention in currency stabilisation led to the inability of capital to be accessed by smaller capital markets. Later, in 2011, larger countries such as Spain and Italy experienced what Blommestein and Hubig (2012), and De Santis (2018) refer to as contagion effects. The result was a widening of sovereign bond spreads across countries that could not be justified by economic fundamentals. These effects later spread into the corporate bond market. During this time, companies experienced previously unprecedented risk premiums associated with their securities. However, these changes were not permanent and represented a temporal event. The widening of bond spreads and deviation from equilibrium price levels has raised concerns about the efficacy of monetary policy in an integrated economic environment (ECB, 2013).

The interbank market was the first market to be affected by the subprime crisis and as a result, was the first market to be investigated during this time from an empirical standpoint. Angel, Harris, and Spatt (2011) argue that the aggregate risk aversion of investors following the default of Lehman Brothers, not the riskiness of the financial institution, contributed most towards widening spreads in interbank lending rates. By estimating the country-specific effects Garcia-de-Andoain, Hoffmann, and Manganelli (2014) show that many banks faced higher funding costs purely due to their nationality. Since the deviations could not be justified, Garcia-de-Andoain et al. (2014) identify these events as instances of financial fragmentation.

Subsequent studies of financial fragmentation focus on the second stage of the global financial crisis and its effect on the government bond market. Research by Georgoutsos and Migiakis (2013) and Battistini, Pagano, and Simonelli (2014) find that fragmentation results from country-specific factors. However, De Santis (2018) argues that deviations are due to contagion effects. The primary unit of measure of financial fragmentation employed in these studies involves comparing credit default swap spreads and sovereign bond yield spreads with the German Bunds.

The duress in the Eurozone market was not contained within banks and financial institutions but spread into the corporate bond market as well. Bedendo and Colla (2015) investigate credit default swap data for 118 non-financial firms and find that a 10% increase in sovereign risk factors corresponds to a 0.5%-0.8% increase in corporate risk. Similarly, Pianeselli and Zaghini (2014) find that instances in which a single-level downgrade in sovereign ratings results in the widening of the corporate bond spread by ten basis points.

Horny, Manganelli, and Mojon (2016) and Zaghini (2016) also study the existence of financial fragmentation in Eurozone corporate bonds. Horny et al. (2016) investigate the pricing of various non-financial corporate bonds originating in Spain, Italy, Germany, and France from 2005 to 2014. Their model employs dummy variables in a simplified approach to measuring cross-border financial fragmentation. They find that German bond spreads are largely integrated with those of French bonds, but differ significantly at times from Italian and Spanish bond spreads, peaking in 2011 and 2012 respectively. Zaghini (2016) looks at over 2400 Euro-based corporate bonds and isolates for the country-specific effects. They find that financial fragmentation peaks during the sovereign debt crisis. Following this, the financial market began to integrate in 2013 and reverted to pre-crisis level in 2014. This reversion effect highlights the temporal nature of financial fragmentation.

2.6 Discussion

Figure 2-12 contains the final taxonomy of market fragmentation proposed in this chapter. It connects the various forms of market fragmentation with their corresponding motivational factors. It also maps the degree of innovation associated with each innovation that leads towards a fragmenting event. Classifying the various types of fragmentation has led to some interesting insights.

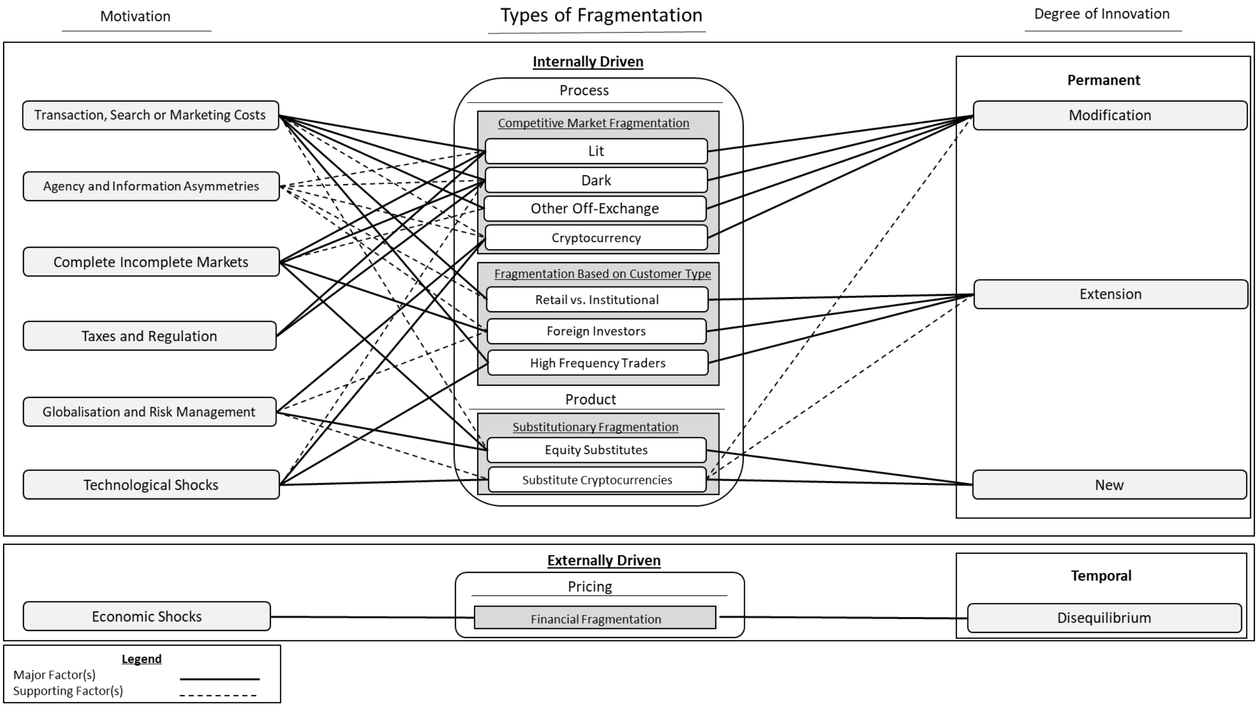

Figure 2-12: Taxonomy of Market Fragmentation (Final)

Firstly, expanding upon the general classifications presented by Avlonitis et al. (2001) and Tufano (1989) resulted in the three Ps of financial fragmentation: process, product, and pricing. Previous taxonomies focus exclusively on internally motivated financial innovations and as a result, only include developments to processes and products. While this does cover the majority of definitions of market fragmentation referenced in the literature, it fails to capture the phenomenon of financial fragmentation. Financial fragmentation is an externally driven event whereby economic shocks result in situations where markets lack perfect integration. Such innovations do not expand upon processes or product offerings and therefore necessitate the creation of an additional category type.

Next, the proposed taxonomy distinguishes between permanent and temporal degrees of fragmentation. Internally motivated innovations (for example, additions and modifications) lead to permanent changes in financial offerings, whether process-based or product-based. Temporal innovations are externally driven and result in the market reverting to previously integrated states once the effects of economic shocks have worn off. For this reason, the taxonomy classifies temporal innovations by a state of disequilibrium, which markets naturally attempt to correct.

Regarding the various motivational factors, the traditional factors presented by Tufano (1989) only encompass process and product innovation types. This is understandable as those are the only two innovation types included in the author's taxonomy. Therefore, a seventh motivational factor, economic shocks, is introduced to classify externally driven sources of market fragmentation.

Changes in regulatory policy are a catalyst in driving fragmentation in equity markets, both lit and dark. They are critical in establishing investor confidence in new exchanges and support subsequent innovations in equity markets. The desire to reduce transaction, search, and market costs motivate innovation, leading to competitive market fragmentation. Transaction cost reduction plays a particularly significant role in the competitiveness of new exchanges and liquidity pools. This is because exchanges use cost savings as a primary marketing tool for attracting liquidity in order to help facilitate the timely execution of transactions. Historically, this has been one of the leading factors influencing fragmentation in quote driven markets. It also continues to be a highly influential factor in more modern forms of competitive market fragmentation, particularly amongst dark pools and cryptocurrency exchanges.

Reductions in information asymmetry are influential in process-oriented innovations; however, they are not the driving force. The desire to complete incomplete markets and well as take advantage of changes in taxes and regulation also only play a supportive role in motivating fragmentation-based process innovations.

Globalisation, risk management, and technological shocks are considered modern motivational factors. They are associated with more recent innovations in market fragmentation such as dark pools, cryptocurrency exchanges and substitutes, and high-frequency trading. They are also the only two factors that play a role in motivating all three types of process and product innovations: competitive market fragmentation, fragmentation based on customer types, and substitutionary fragmentation.

The degree of fragmentation is different across the various types of fragmentation. Competitive market fragmentation events largely represent a modification to existing services. These events are also the most plentiful; therefore, it is understandable that they represent the degree of innovation that is the least costly to implement. Fragmentation based on customer types exclusively focuses on extending upon existing services. These events largely occur within traditional exchanges and allow investors to participate in such submarkets in addition to using traditional mediums of exchange. Innovations that represent completely new financial products are the most expensive to implement and consequently, they are also the least plentiful.

2.7 Conclusion

This chapter addresses RQ1 and discusses the various forms of fragmentation and how they relate to financial innovation. The result of the study is a unique taxonomy of the innovations that lead to fragmentation in financial markets. This framework identifies how the existing literature, both theoretical and empirical, interprets the impact of such events on their respective financial markets. The taxonomy highlights that not all innovations, including the motivating factor that lead to them, are created equal. Some markets, such as those for substitutes to traditional equity investments, are more innovative as they are more focussed on the creation of new investable products. Comparatively, traditional equity markets, or those that operate in an exchange structure, are less innovative and focus on small modifications to traditional services that aim to serve a particular subset of the market with particular trade preferences such as speed and anonymity.

The final model adapts the taxonomies presented by Avlonitis et al. (2001) and Tufano (1989), expanding upon the process and product classifications of financial innovation. The addition of a third classification, pricing, is proposed resulting in the development of the three Ps of financial innovation: process, product, and pricing. These classifications are used to identify and categorise the various forms of fragmentation referenced in the literature and results in the creation of four fragmentation classes: competitive market fragmentation, fragmentation based on customer type, substitutionary fragmentation, and financial fragmentation. Instances of innovation in all fragmentation classes, except for financial fragmentation, are classified as internally motivated and result in permanent changes to financial markets. Financial fragmentation is the only temporal event and pertains to markets reaching a state of disequilibrium, which they correct for naturally over time.

The review identified a series of fragmenting events within each fragmentation class. The extant research on each fragmentation subclass reviewed to identify the motivational factors that influence their development. This chapter explores the implications of the various fragmentation events on market conditions, including liquidity and price discovery. A desire to reduce transaction costs for investors motivates most innovations leading to market fragmentation. More modern motivational factors exert greater influence over recent fragmenting innovations. Technological shocks and globalisation are most responsible for fragmenting events involving dark pools, cryptocurrencies, and high-frequency trading.

The degree of innovation is associated with the type of fragmentation. Competitive market fragmentation events involve modification of existing services, while fragmentation based on customer types involve the extension of existing services. In contrast, substitutionary fragmentation results in innovations of new financial products that differ from existing financial products.

Reductions in information asymmetry play a supporting role in motivating many events that fragment marks. It is also a by-product of many fragmenting events such as lit and dark market fragmentation as well as the introduction of high-frequency trading and equity substitutes. As a result, market fragmentation coincides with changes to the price discovery process as more or less permanent price-adjusting information is made public in a timely fashion. This effects investor decision making as public price and quote signals become more or less reliable. Events that negatively impact the accuracy of publicly available information jeopardise markets as they discourage investor participation or encourage greater risk aversion.

Drawing on this taxonomy, the empirical studies reported in Chapters 3 and 4 of this thesis explore the impact of key fragmenting events on the price discovery process. Specifically, the following chapters focus on the extent to which transaction prices and order book quotes fully reflect all relevant information. Chapter 3 reports an empirical study that focusses on competitive fragmentation within and across lit and dark order books and measures the impact on the informativeness of transaction prices and mid-quotes. Chapter 3 measures levels of price discovery (information asymmetry) and tests the extent to which efficient market hypothesis applies in explaining these changes. Chapter 4 reports an empirical study that tests the applicability of equity-based efficient market theories to competitive fragmentation in cryptocurrency markets. The objective of these two empirical studies is to assess the efficacy of existing theory, rooted in traditional equity markets, on a new asset class.

Chapter 3: Fragmentation and Price Discovery in Equity Markets

3.1 Introduction

Access to liquidity has evolved for equity investors since the turn of the century. Historically, a single quote-driven exchange would advertise prices and quantities of shares available for sale and purchase. Investors would submit limit orders to the exchange knowing the current state of the order book. In contrast, today's market participants access liquidity across multiple exchanges. Motivated by a desire to reduce transaction and search costs, new equity exchanges formed, resulting in events of competitive fragmentation in equity markets. The desire to fill gaps in exchange services and cater to the needs of a heterogeneous investor base and support market completeness also played motivating roles (see Figure 2-12).

Improvements to market completeness are resulted from exchanges allowing investors access to both traditional and un-advertised liquidity herein referred to as 'lit' and 'dark', respectively, also resulted in instances of competitive market fragmentation. Dark liquidity differs from lit liquidity as it offers no pre-trade transparency. Dedicated dark liquidity providers are known as 'dark pools' and are the primary source of dark liquidity. This chapter investigates the impact that fragmentation within and across lit and dark exchanges has on the price discovery process. When information regarding the fundamental value of an asset leaves the primary exchange, it has a detrimental effect on investors' ability to formulate accurate prices and impedes market efficiency (L. Ye, 2016; M. Ye, 2012; Zhu, 2014). Therefore, this chapter uses rational expectations theory and the efficient market hypothesis as frameworks to study the extent to which competitive market fragmentation coincides with the dispersal or concentration of valuable price-adjusting information.

The introduction of the Markets in Financial Instruments Directive (MiFID) prompted events of competitive market fragmentation in the European equity market by eliminating barriers to entry for new exchanges. Three policies contained within MiFID are responsible for the majority of the changes in the microstructure of the market. The first policy retracts the 'concentration' and 'default' rules which discourage fair competition amongst exchanges by, under many circumstances, requiring the routing of orders to the primary exchange. The second policy sets minimum transparency standards for exchanges regarding the publication of pre- and post-trade information. The third policy introduces the best-execution rule and guarantees investors that their trades will not execute at a price that is less favourable than the one available on the primary exchange.[11] By providing protections for investors who trade outside of the primary exchange, MiFID encourages the formation of new exchanges called Multilateral Trading Facilities (MTFs). MTFs offer investors an alternative source of both traditional lit and dark liquidity for European equities.[12]

While the term 'dark' liquidity is considered a recent development, the overall concept behind this type of liquidity is not. Dark liquidity exists on traditional exchanges through upstairs/over-the-counter (OTC) markets, in addition to dedicated providers (dark pools). OTC markets do not report information regarding the existence of a trade or the availability of liquidity until after the completion of a successful transaction. The lack of pre-trade transparency means that unsuccessful transactions do not reveal the availability of liquidity unless the order is later routed to a traditional lit exchange. Exchanges also offer investors access to hidden order types to allow for reduced pre-trade transparency within a lit order book (see Section 2.2.3). Other historical forms of dark liquidity include the following: floor broker orders, specialist capital on floor-based exchanges, working orders handled by agency brokers or broker-dealers, dealer capital, stand-alone crossing networks, and broker or exchange/ECN operated crossing networks (Buti et al., 2011).[13]

The key difference between dark pools and other means of off-exchange trade execution is that dark pools operate under complete pre-trade transparency. Only dark pools preclude the need for broker or dealer involvement, thus preventing any information leakage. Since dealers in the OTC market contact other dealers in order to source liquidity, complete pre-trade opacity cannot be guaranteed. Another difference between dark pools and the OTC market is the trading cost, which is theoretically lower in dark pools (Lefebvre, 2010). See Appendix 1 for a more detailed discussion about the characteristics of dark pools.

In the paper 'Do Dark Pools Harm Price Discovery?' Zhu (2014) acknowledges that although OTC liquidity is not usually classified as dark, it is still a source of non-displayed liquidity. Given the similarity between traditional OTC orders and orders submitted to dark pools, this study reports analysis both including and excluding off-order book transactions.

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[11] Exchanges may also opt to use the best price available across the consolidated European market. See Appendix A1.4 for more information about order matching and execution.
[12] MTFs are not limited geographically and can trade in European assets regardless of their country of origin.
[13] The first exchange that was successful at automating the process was created by Instinet which had been running, with limited success, an ECN since 1969.

3.2 Existing Literature

There exists extensive research, both theoretical and empirical, surrounding the efficient market hypothesis and rational expectations theory relating to price discovery, liquidity and asymmetric information. The seminal works around which the majority of research revolves are Kyle (1985) and Glosten and Milgrom (1985) who focus on non-fragmented markets. Kyle (1985) studies the liquidity characteristics of markets as well as the informational role that prices, particularly those that stem from informed competitive traders, play in said markets. The author concludes that the level of uninformed noise trading is proportional to the depth of the market and has an inverse relationship with the level of private information that has yet to be compounded into prices. Glosten and Milgrom (1985) deduce that increased participation from informed competitive traders is proportional to bid-ask spreads due to adverse selection. The transfer of wealth from uninformed to informed investors plays a critical role in maintaining price efficiency and is, therefore, crucial to the process of price discovery. This transfer of wealth is compensation to informed investors in return for gathering price revealing information and conveying it to the market and thus contributing to price discovery.

The papers mentioned above play a foundational role in future studies and are the cornerstone for theory examining the relationship between competitive market fragmentation and price discovery. This chapter measures three forms of competitive market fragmentation and examines their impact on the price discovery process. The three forms of competitive market fragmentation are as follows: i) intra-market fragmentation within the lit market, ii) inter-market fragmentation between lit and dark markets, and iii) intra-market fragmentation within the dark market (see Figure 3-1). Intra-market fragmentation within the lit market (i) occurs when new exchanges operating displayed order books are introduced into the market.

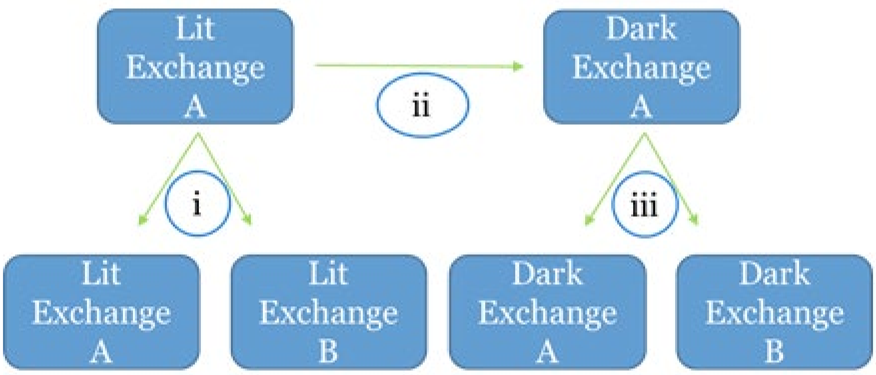


Figure 3-1: Three forms of Competitive Market Fragmentation

This section reviews existing literature of each of the aforementioned forms of fragmentation with market quality metrics such as liquidity and price discovery and outlines the contributions to the body of research. Section 3.2.1 focuses on the exclusively on fragmentation between lit exchanges (i) while Section 3.2.2 discusses fragmenting events involving dark exchanges, (ii) and (iii).

3.2.1 Intra-market Lit Fragmentation

Intra-market lit fragmentation refers to increased levels of competition amongst exchanges with displayed order books (see (i) in Figure 3-2). This form of competitive market fragmentation occurs when new lit exchanges open and offer investors additional choices for where they can submit orders. Findings regarding the benefits of fragmentation within lit order books are mixed; however recent studies find that fragmentation is beneficial to the price discovery process (R. H. Battalio, 1997; B. Boehmer & Boehmer, 2003; Colliard & Foucault, 2012; Foucault & Menkveld, 2008). Studies also acknowledge that benefits observed across the consolidated global order book come at the expense of the local exchange (Degryse et al., 2015; Gresse, 2017).[14]

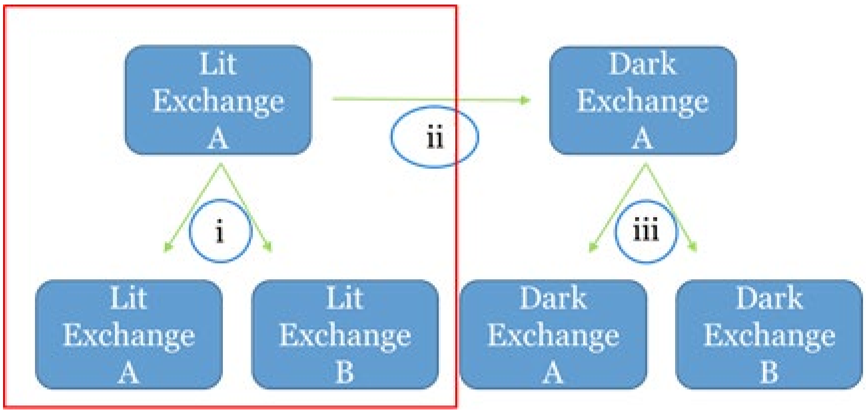


Figure 3-2: Three forms of Competitive Market Fragmentation (Lit)

Traditional studies view exchanges as natural monopolies where participants benefit from economies of scale. Transaction costs in a monopolistic environment are reduced through the superior matching of buyers and sellers (Chowdhry & Nanda, 1991; Mendelson, 1987; Pagano, 1989). Critics of market fragmentation in traditional lit exchanges argue that adverse selection risk increases and price discovery deteriorates as investor access to exchanges with pre-trade transparency increases. Mendelson (1987) states that participants face more

[14] The local exchange refers to the dominant sovereign exchange (primary exchange) while the the global order book is comprised of orders across all exchanges trading in a particular stock.

difficulty finding a counterparty to their trade in a fragmented clearinghouse market compared to a consolidated clearinghouse market. Trade execution speeds decrease, leading to increased price variance and lower returns on trades, when finding a counterparty becomes more difficult. Greater participation by a wide array of investors improves both the probability and speed of execution. As a result, investors favour and tend to concentrate on the most liquid market, resulting in a positive feedback loop (Pagano, 1989).

Pagano (1989) adds that if two similar exchanges exist with unequal trading costs, some investors will concentrate on one exchange while others migrate to the alternative exchange. Migrating investors are typically large traders who are forced to independently find a trading partner in order to avoid adverse price changes. This concept stems from a theory by Keynes, which states that a key characteristic of a functioning market is its ability to avoid adverse price changes when facilitating a transaction. Since trading volume is positively related to the absorptive capacity of a market, any events which draw speculators away from an exchange will adversely affect liquidity (Pagano, 1989).

While the previously discussed theories are true the individual exchanges, Mendelson (1987) argues that the overall quality of price signals improves in the consolidated global market. Investors who can access the order books of multiple exchanges simultaneously will experience a reduction in the weighted average price variance. This occurs as the price diversification effect dominates the 'thinness' effect[15] in each exchange.

Chowdhry and Nanda (1991) extend the work of Kyle (1985) by incorporating multiple exchanges into their model. They find that adverse selection risk increases along with an increase in the number of exchanges listing a particular asset. The increase in adverse selection risk hinders a market's ability to formulate accurate prices (Chowdhry & Nanda, 1991; Madhavan, 1995). When there exists a greater proportion of large liquidity traders who can simultaneously access multiple exchanges, exchanges experience an increase in volume but also a decrease in the informativeness of prices. Prices become less informative as market makers, who compete by offering investors more favourable transaction costs than their competitors, release price information to the market in order to deter informed trading. Smaller liquidity traders tend to concentrate on exchanges that offer lower transaction costs. Consequently, the actions of smaller liquidity traders attract large liquidity traders and

[15] 'Thinness' implies a lack of depth, that is, few shares being advertised in the order book at the best price level.

informed traders, thereby concentrating the market around a single dominant venue (Chowdhry & Nanda, 1991).

Madhavan (1995) argues that differences in trade disclosure rules are largely responsible for the fragmentation of markets and that markets with similar requirements across exchanges tend to consolidate. Fragmented markets allow dealers to be less competitive. Fragmented markets also help informed traders conceal their trades from certain participants of the overall consolidated market. Less competition among dealers and more dispersed informed trading can contribute to price volatility (Madhavan, 1995). Easley et al. (1996) and Bessembinder and Kaufman (1997) also conclude that increased fragmentation, caused by the listing shares on multiple exchanges, deteriorates the price discovery process of the primary exchange. This occurs as the most profitable uninformed trades are picked off by informed traders, often referred to in the literature as 'cream-skimming'.

One drawback of the studies mentioned up to this point is their use of specialist markets. In specialist markets, market makers or dealers take on the responsibility of providing quotes and matching purchase and sale requests. In contrast, electronic limit order books allow market participants to trade with each other directly without the need for an intermediary. Hasbrouck (1995) develops a widely used measure of price discovery, the information share (IS). Hasbrouck (1995) concludes that, for those shares whose primary listing is on the New York Stock Exchange (NYSE), the primary exchange is responsible for over 90% of price discovery when compared to regional satellite exchanges on which the asset is cross-listed. Barclay et al. (2008) later find that consolidating orders aids in producing efficient prices and is particularly important when the demand for liquidity is high.

Empirically, critics of market fragmentation in displayed order books show that price efficiency is inversely related to the level of fragmentation in the market. Bennett and Wei (2006) study 39 stocks that transfer their primary listing from a fragmented market (NASDAQ) to a consolidated market (NYSE) between 2002 and 2003. They find that the transition to a consolidated market improves price efficiency and liquidity provisions. They also observe improvements to price efficiency through reduced volatility and a contraction of quoted, effective and realised spreads. Gajewski and Gresse (2007) confirm the improvements to price efficiency. They find that consolidated order books offer lower trading costs compared to orders which are shared between a limit order book and a group of competing dealers.

Foucault and Menkveld (2008) examine the launch of the Frankfurt Stock Exchange (FSE) operated EuroSets into the Dutch stock market alongside the existing EuroNext exchange and present mixed results. The authors investigate whether liquidity improves upon the introduction of a new market and conclude that the consolidated global limit order book deepens following the introduction of EuroSets. However, higher trade-through rates in the newly formed market highlight the need for policies protecting the price priority of limit orders in order to preserve the quality of transactions (Foucault & Menkveld, 2008).

In contrast, Riordan, Storkenmaier, and Wagener (2011) find that price protection policies are not necessary to protect all investors. They study the events surrounding the introduction of three new Multilateral Trading Facilities (MTFs) operating lit order books: Chi-X, BATS and Turquoise. They find that a lack of price protection policies did not prevent investors from executing orders at the best price level. Riordan et al. (2011) argue that given the importance of price competition, investors prioritise the need to stay informed by autonomously monitoring multiple markets. However, Riordan et al. (2011) concede that some investor protection policies are necessary. Not all market participants, particularly retail investors, can afford to employ the monitoring techniques needed to avoid the increase in trade-through rates.

Advocates of market fragmentation argue that it has positive market effects and increases investor welfare. Monopolistic trading environments often result in non-competitive behaviour. Increased competition improves trading costs in the form of tighter primary market bid-ask spreads as liquidity suppliers improve their prices (R. H. Battalio, 1997; B. Boehmer & Boehmer, 2003; Colliard & Foucault, 2012; Foucault & Menkveld, 2008). R. H. Battalio (1997) study the New York Stock Exchange (NYSE) after the introduction of a third-market broker deal and the results support trading cost benefits of fragmentation. B. Boehmer and Boehmer (2003) study the NYSE following the listing of Exchange Traded Funds (ETFs) on the competing American Stock Exchange (ASE) and also support the positive benefits of fragmentation.

O'Hara and Ye (2011) are among the first studies to directly compare the effects of fragmentation on liquidity. Using data on 265 stocks over six months in 2008, they find that higher levels of fragmentation are inversely related to both transaction costs and the speed of execution. While the authors acknowledge that more fragmented assets experience greater short-term volatility, this comes with the benefit of improved market efficiency. Using data for 100 FTSE stocks from 2008 to 2011, Boneva, Linton, and Vogt (2016) find that volatility is lower in a fragmented lit order book. Volatility also remains more constant over the study period when compared to the effects of dark order book fragmentation. One drawback to the study by O'Hara and Ye (2011) is that the data does not allow for the comparison between global consolidated and local primary order books. However, O'Hara and Ye (2011) argue that the positive effects are because the overall market acts as a single source of liquidity with multiple entry points. This concept is explored in future studies by Degryse et al. (2015) and Gresse (2017).

Degryse et al. (2015) study a sample of 52 large and midcap constituents of the Amsterdam Exchange (AEX) Index from 2006 to 2009. They conclude that fragmentation in the displayed (or lit) order book is beneficial, with regards to liquidity, to the consolidated global order book but detrimental to the primary exchange. Gresse (2017) extends the work of Degryse et al. (2015) by sampling data from more active European markets. Gresse (2017) gathers data on large and midcap U.K. and Euronext stocks and finds that results vary depending on the size of the firm. Following the introduction of MiFID, spread and depth measures either improve across both consolidated and local markets or are unaffected. High-value stocks and those with less electronic trading experience the greatest benefits. However, lit fragmentation is detrimental to the depth of low-value stocks while algorithmic trading is largely to blame for any decreases to depth for high-value stocks.

Some authors acknowledge that fragmentation is beneficial to the market only up to a certain point. Degryse et al. (2015) find that visible fragmentation follows an inverted U-Shape showing with the marginal benefit of fragmentation decreasing over time. They determine that the ideal level of fragmentation of 32% as measured by one minus the Herfindahl-Hirschman Index. They find that fragmentation improves liquidity about the midpoint but has a lesser effect deeper in the visible order book.

In summary, the results surrounding the benefits of fragmentation within lit order books are mixed. Recent studies find that fragmentation is beneficial to the price discovery process (R. H. Battalio, 1997; B. Boehmer & Boehmer, 2003; Colliard & Foucault, 2012; Foucault & Menkveld, 2008). However, benefits observed across the consolidated global order book come at the expense of degradation to the local exchange and retail investors (Degryse et al., 2015; Gresse, 2017).

3.2.2 Inter-market Fragmentation and Intra-market Dark Fragmentation

This section explores existing research in the price discovery implications of inter-market fragmentation and intra-market dark fragmentation (see ii and iii in Figure 3-3). Existing studies, both theoretical and empirical, differ significantly regarding the price discovery and liquidity effects of reduced order-book transparency, including the migration of orders from lit to dark markets. The migration of orders from lit to dark markets, and vice versa, is herein referred to as inter-market fragmentation. Except for Majtyka, Henker, and Henker (2015), there are no studies of intra-market dark fragmentation. Also, unlike the work in this chapter, Majtyka et al. (2015) focus on the effects of intra-market dark fragmentation on liquidity as opposed to price discovery.

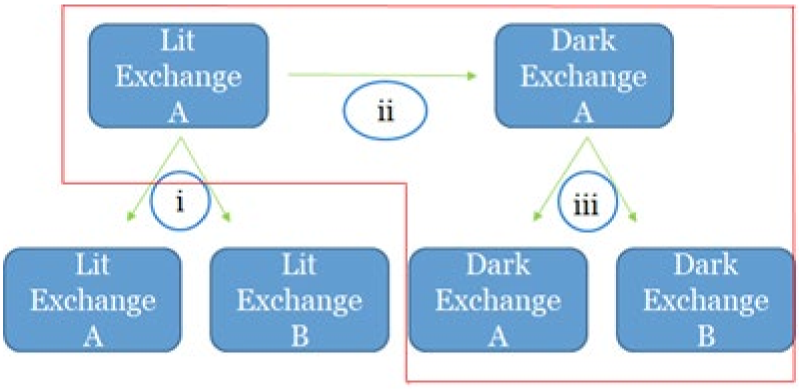


Figure 3-3: Three forms of Competitive Market Fragmentation (Dark)

Post-Trade Transparency

Early research surrounding the transparency of equity markets focusses on post-trade transparency, that is, the disclosure of transactions. Madhavan (1995) shows that, under the condition of voluntary trade disclosure, markets can remain fragmented and only consolidate when trade disclosure is made mandatory. Since traders are heterogeneous in their trading requirements, markets will fragment in order to meet their demands (L. E. Harris, 1993). Supporting the needs of heterogeneous investors drives the market towards a state of completeness. Madhavan (1995) finds that large traders front-run their trades in a consolidated market resulting in greater execution costs for smaller investors. As a result, all investors benefit from dynamic trading in a fragmented environment where trade disclosure is not required. Dealers also benefit from fragmentation as they face less competition than in a consolidated market. The resulting fragmentation leads to greater price volatility and less efficient prices (Madhavan, 1995).[16] Intraday bid-ask spreads also widen as, unlike in a transparent consolidated market, dealers face greater uncertainty over time due to the lack of trade disclosure. Small traders, however, prefer to have access to more information before trading and thus benefit from a consolidated market with greater transparency (Madhavan, 1995). Experimental findings reported by Bloomfield and O'Hara (1999, 2000) also find that greater market transparency, most notably trade disclosure, improves market liquidity and reduces price volatility resulting in improvements to price efficiency.

Naik, Neuberger, and Viswanathan (1999) propose that the benefits of post-transparency come at a cost. Greater transparency reduces adverse selection through the sharing of quantity risk by limiting the winning dealer's ability to manipulate the beliefs of other dealers. The downside of this is a reduction in public welfare through greater exposure to price revision risk where prices become more sensitive to the information revealed during trade negotiations.

Pre-trade Transparency & Price Discovery

The focus now shifts to research surrounding pre-trade transparency. In auction and dealer markets, pre-trade transparency allows market makers to learn information more quickly. This improved access to information allows market makers to price assets more efficiently and lower trading costs for uninformed traders (Pagano & Röell, 1996). Unlike previous studies (Admanti & Pfleiderer, 1991; Madhavan, 1995) Pagano and Röell (1996) do not require the identities of traders to be known by market makers, thus aligning their resulting more closely with real world scenarios. Baruch (2005) supports improvements to price discovery and liquidity, including bid-ask spreads and argues that a transparent market allows participants to more easily compete with liquidity providers. Boehmer, Saar, and Yu (2005) provide empirical support for Baruch (2005). They study the introduction of NYSE's OpenBook, where pre-trade transparency increases for off-floor traders who are provided with limit-order book information. Eom et al. (2007) find similar results surrounding the publication of additional levels of the order book on the Korea Exchange.

In contrast, Boulatov and George's (2013) model suggests price discovery improves when liquidity providing orders are concealed. The improvement occurs as informed traders compete more aggressively to provide liquidity. Foley and Putniņš (2016) provide further

[16] Madhavan (1996) requires the market to be sufficiently large for the results to hold true and the findings are reversed for smaller markets.

evidence on the role of dark trading. Consistent with the theoretical model of Boulatov and George (2013) they find that two-sided dark trading improves market quality by encouraging competition between liquidity suppliers. Madhavan, Porter, and Weaver (2005) support this contradiction with their investigation into the Toronto Stock Exchange's decision to reveal the first five levels of the order book to the public. The authors attribute the drop-in liquidity to limited order traders who are now less inclined to provide 'free trading' options to other traders.

Bloomfield and O'Hara (1999) conduct an experimental study to investigate the effects of both pre- and post-trade transparency on price discovery and liquidity. They find that post-trade transparency increases price efficiency at the cost of wider bid-ask spreads. Post-trade transparency requirements de-incentive market makers from competing for liquidity. However, pre-trade transparency has no significant effect on markets (Bloomfield & O'Hara, 1999; Bloomfield et al., 2005).

Hendershott and Mendelson (2000) shift their focus to modelling the interaction between dealer networks and a particular subset of dark pools, passive crossing networks. Their research aligns with the work presented in this chapter as it investigates the effects that both transparency and inter-market fragmentation have on market performance. Hendershott and Mendelson (2000) find two opposing effects of the introduction and growth of a crossing network. On the positive side, a crossing network's liquidity improves as trading volumes increase, which in turn attracts additional liquidity until the crossing network reaches a 'critical mass'. On the negative side, the absence of price priority leads to a 'crowding' effect whereby trades compete for execution on the same side of the market. Hendershott and Mendelson (2000) find that investors who use the dealer market as a last resort compel dealers to widen bid-ask spreads. Prices also become more efficient so long as the information is short-lived.[17] Traders who only use crossing networks, however, provide a counterbalancing effect. They contribute to reducing adverse selection by attracting new liquidity and providing an alternative to the dealer market for informed investors. This results in narrower bid-ask spreads and less efficient pricing.

In an extension of the classical rational expectation model by Kyle (1985), M. Ye (2012) studies the market outcome when informed traders have the option of sending their trades to either a displayed limit order book, that is, to a traditional lit exchange, or a crossing network,

[17]The opposite effect can be observed upon the introduction of a crossing network if the information is long-lived.

which is a particular type of dark pool. Informed traders value the ability to hide their trades. Therefore, the routing of informed orders to a crossing network reduces price discovery, with the impact being higher for stocks with higher fundamental value uncertainty. M. Ye (2012) also concludes that the use of a crossing network harms price discovery if informed traders can trade in the crossing network. The model implies that inter-market fragmentation between crossing networks and traditional lit exchanges increases until informed investors are indifferent between non-execution probability in the crossing networks and price impact in the traditional exchange (M. Ye, 2012).

Zhu (2014) develops a similar model but, unlike M. Ye (2012) who assumes exogenous choices of trading venues by liquidity traders, assumes endogenous venue choices by liquidity traders. This assumption of endogenous venue selection is critical to the resulting findings. The study improves on other models that exogenously fix the strategies of informed traders (Hendershott & Mendelson, 2000) or fail to consider the role asymmetric information plays regarding to the value of the asset (Buti et al., 2017; Degryse et al., 2009). Zhu's (2014) model results in informed investors clustering on the heavy side of the market, thereby facing low execution probability in the dark pool, relative to uninformed traders. This occurs because informed orders are positively correlated with the value of the asset, and therefore each other. As a result, traditional exchanges become more attractive to informed investors, improving the price discovery process by concentrating price-relevant information on the exchange. However, greater price discovery comes at the cost of greater adverse selection risk and wider bid-ask spreads. Dark pools also become more attractive to uninformed investors as liquidity orders are less likely to correlate with each other. Therefore, uninformed investors are able to maintain a higher probability of execution compared to informed investors.

L. Ye (2016) extends upon Zhu (2014) to include noisy information. Under a noisy information structure, L. Ye (2016) finds that the majority of informed traders opt to trade in the dark pool, thereby impairing price discovery. However, in the circumstances with minimum noise where the level of information risk is low, the results coincide with those of Zhu (2014); the majority of informed traders transact in the exchange and the price discovery process is improved. Unlike M. Ye (2012), L. Ye (2016) also allows uninformed traders to choose between exchanges. Removing this choice aligns the results with that of M. Ye (2012).

Empirical research studying the impact of dark liquidity transactions on price discovery is limited. Hendershott and Jones (2005) use empirical data from the Island electronic communication network (ECN) and find a negative impact surrounding the exchange's 2002 elimination of pre-trade transparency. The reduction in pre-trade transparency results in an increase in transaction costs and adverse selection within the exchange. It also negatively impacts the exchange's market share and contribution to price discovery. Competing exchanges, however, benefit from the change through a reduction in trading costs.

Comerton-Forde and Putniņš (2015) conduct the most direct empirical analysis of dark trading and its impact on price discovery. The authors use Australian data from the ASX All Ordinaries index from 1 February 2008 to 30 October 2011 from the Australian Stock Exchange (ASX) and Chi-X exchanges. Their results are in line with Zhu (2014) and indicate that increased inter-market fragmentation impedes price discovery as orders bypass pre-trade transparency requirements. Comerton-Forde and Putniņš (2015) also find that prices become less efficient as order flow migrates from lit to dark trading venues when the proportion of non-block dark trading exceeds 10%. The incentive to engage in costly information acquisition decreases as prices become less efficient, which causes a further reduction in the informational efficiency of prices. High levels of dark trading also increase adverse selection and widen of bid-ask spreads in the primary lit market as uninformed trading in the lit market reduces disproportionally. Hatheway et al. (2017) find support for these findings using a data set consisting of 59 NYSE and 57 NASDAQ stocks over three months beginning January 3rd 2011.

Comerton-Forde and Putniņš (2015) also find that dark trading increases the role order book quotes play in determining prices compared to trade prices. Increased informational content in order book quotes implies that liquidity providers in the lit market are becoming increasingly more informed. When the dark liquidity market share is below 10%, however, they find that inter-market fragmentation across lit and dark order books improves price discovery within the primary exchange. The changes in outcome surrounding the 10% dark market share threshold imply that price discovery is an increasing concave function (Comerton-Forde & Putniņš, 2015).

Pre-trade Transparency & Liquidity

The following studies focus on the liquidity and performance impacts of increased dark trading. Some of the later studies (Brandes & Domowitz, 2011; Buti et al., 2011; Nimalendran & Ray, 2014) use their results to infer the effect on price discovery. This is important as the impact of dark trading on price discovery is not necessarily the same as the impact of dark trading on liquidity (Zhu, 2014).

Degryse et al. (2009) construct a model containing a dealer market and crossing network. They study the impact of various levels of transparency surrounding historical order flow on investor behaviour and welfare. Degryse et al. (2009) find that the ability to predict order flow varies with the level of transparency. However, they do not find that overall market returns benefit from adding a crossing network or increasing transparency in the dealer market. The lack of improved market return results varies depending on the asset's relative spread.

Gresse (2006) uses data from July 2000 to June 2001 for the London Stock Exchange's SEAQ (dealer market) as well as the POSIT crossing network. The author finds that bid-ask spreads are inversely correlated with dealer volume on the crossing network for dealers. The effect is reversed, though less pronounced, for institutional investors. Overall, liquidity improves in the lit exchange as any cream-skimming effects resulting from uninformed trading by institutional investors are more than offset by the risk-sharing benefits experiences by dealers. A subsequent study, Gresse (2017), finds dark liquidity has either a positive effect on liquidity or no effect at all. However, Gajewski and Gresse (2007) find that dark trading by dealers in a hybrid market may be detrimental to liquidity when compared with lit fragmentation. Degryse et al. (2015) support Gajewski and Gresse (2007) and concur that negative effects associated with increased dark liquidity use are consistent with 'cream-skimming'. This occurs as dark pools attract predominately uninformed orders resulting in increased adverse selection on the lit exchange.

Unlike the previous study by Degryse et al. (2009), Buti et al. (2017) model the interaction between a crossing network and limit order book. They find that introducing a crossing network increases overall trading activity. However, increased trading activity comes at the expense of wider (narrower) bid-ask spreads when the order book is deep (shallow), lower depth, and a decrease in overall returns. Some investors benefit from the crossing network as those that are able to utilise it for trading experience greater gains.[18] A previous empirical study by Buti et al. (2011) uses 2009 data from 11 U.S. dark pools and measures the effects dark pools have on price liquidity and price efficiency. Time-series results show a positive relationship between dark pool market shares and total trading volume, depth and bid-ask

[18] L. Ye (2016) improves upon the two previous models by allowing for both endogenous pricing and dynamic venue selection.

spreads. The results also show a negative relationship dark pool market shares and volatility, returns and order imbalance. Cross-sectional results show an inverse relationship between dark pool market shares and bid-ask spreads, price impact, and volatility..[19] Boneva et al. (2016) also find a negative relationship between dark liquidity market share and volatility. Price efficiency results, however, are unclear.

Nimalendran and Ray (2014) use proprietary crossing network transaction data from 1 June 2008 to 31 December 2009 to examine information linkages between dark and lit exchanges. Using transaction-level crossing data from an actual crossing network, they gain insight into the exact nature of dark pool trades. However, drawing data from a single source limits its generalizability. Nimalendran and Ray (2014) find that dark trading positively correlates with bid-ask spreads and price impacts in the lit exchange. They also conclude that, in addition to lit exchanges, crossing networks provide a venue for informed traders to trade strategically. As a result, Nimalendran and Ray (2014) propose that dark pools contribute to the price discovery process. The extent to which the price discovery process is supported, however, depends on the nature of the trade. Trades in less liquid stocks against members of the crossing networks transmit significant information to the lit exchange. However, trades in liquid stocks, trades by the crossing network's brokerage desk, and large blocks in negotiated crosses transmit less information.

Brandes and Domowitz (2011) support the findings of M. Ye (2012) and Nimalendran and Ray (2014). They study dark pool trading in Europe and find that increased dark trading is beneficial to price discovery. Using 2009 data from U.S. trade reporting facilities, O'Hara and Ye (2011) find that increased inter-market fragmentation through the use of dark liquidity leads to more efficient prices which more closely resemble a random walk. They also find a negative relationship between dark pool market shares and bid-ask spreads.[20]

Over-The-Counter Trades

The level of pre-trade transparency is slightly greater for over-the-counter (OTC) transactions compared to dark pool transactions. While they do not publish their information to the lit limit order book, OTC trades require broker-dealers to negotiate terms among parties whenever they choose not to trade against then own account. Seppi (1990) discusses how

[19] Ray (2010) uses POSIT, Liquidnet, and Pipeline data from June 2005 to June 2005 and finds that a cross-sectional study results in a concave relationship between dark pool market share and overall market quality.

[20] Comerton-Forde and Putniņš (2015), Degryse et al. (2015), and Hatheway et al. (2017) observe that bid-ask spreads widen as dark pool market shares increase while O'Hara and Ye (2011) and Ready (2014) find evidence of the opposite effect.

uninformed traders benefit from the lack of anonymity in the OTC market when trading large blocks while informed traders prefer to use traditional lit exchanges. Madhavan and Cheng (1997) and Booth et al. (2002) support Seppi (1990), empirically concurring with the conclusion that uninformed liquidity based trades favour the OTC market.

The OTC market is viewed as a source of unexpressed trading interest and as a result contains untapped liquidity (Grossman, 1992). Through the negotiation process, large block trades in the OTC market can be revealed as liquidity-driven, encouraging trade by reducing adverse selection risk (Bessembinder & Venkataraman, 2004; Madhavan & Cheng, 1997). When allowed to execute off-exchange, whether in the OTC market or a dark pool, liquidity motivated block trades do not cause temporary deviations from the expected price. Therefore, liquidity-based OTC trades do not adversely impact the price discovery process.

In summary, early research surrounding post-trade transparency in equity markets shows that markets can remain fragmented and only consolidate when trade disclosure is made mandatory (Madhavan, 1995). Fragmentation caused by differing levels of post-trade transparency leads to greater price volatility and less efficient prices (Madhavan, 1995).[21] Bloomfield and O'Hara (1999, 2000) also find that greater post-trade transparency improves market liquidity and reduces price volatility, which increases price efficiency. Greater transparency reduces adverse selection but results in greater exposure to price revision risk (Naik et al. (1999)

Baruch (2005) supports improvements to price discovery and liquidity, including bid-ask spreads and argues that a transparent market allows participants to more easily compete with liquidity providers. Boehmer, Saar, and Yu (2005), Baruch (2005), and Eom et al. (2007) find that price discovery improves on the lit exchange with greater pre-trade transparency. Hendershott and Mendelson (2000) find that investors who use the dealer market as a last resort compel dealers to widen bid-ask spreads.

M. Ye (2012) also concludes that the use of a crossing network harms price discovery if informed traders can trade in the crossing network. Zhu (2014) improves on other models that exogenously fix the strategies of informed traders (Hendershott & Mendelson, 2000) or fail to consider the role asymmetric information plays regarding to the value of the asset (Buti et al., 2017; Degryse et al., 2009). Zhu's (2014) model results in informed investors

[21] Madhavan (1996) requires the market to be sufficiently large for the results to hold true and the findings are reversed for smaller markets.

clustering on the heavy side of the market, thereby facing low execution probability in the dark pool, relative to uninformed traders. L. Ye (2016) extends upon Zhu (2014) and finds that the majority of informed traders opt to trade in the dark pool, thereby impairing price discovery.

The OTC market is viewed as a source of unexpressed trading interest and as a result contains untapped liquidity (Grossman, 1992). Through the negotiation process, large block trades in the OTC market can be revealed as liquidity-driven, encouraging trade by reducing adverse selection risk (Bessembinder & Venkataraman, 2004; Madhavan & Cheng, 1997).

3.3 Problem, Contribution and Hypotheses

Market participants access liquidity across multiple exchanges. Given the research reviewed in Section 3.2, it is clear that market fragmentation impacts investors' ability to formulate accurate prices (M. Ye, 2012; Zhu, 2014; L. Ye, 2016). This chapter identifies three forms of competitive market fragmentation: i) intra-market fragmentation within the lit market, ii) inter-market fragmentation between lit and dark markets, and iii) intra-market fragmentation within the dark market (see Figure 3-1). Using rational expectations theory and the efficient market hypothesis, this study examines RQ2 and the extent to which competitive market fragmentation dilutes price-adjusting information within lit exchanges. In doing so, the study contributes to the existing literature on intra-market fragmentation. It tests whether the structure of the 'lit' exchange impacts the informativeness of its trades and quotes when presenting investors with more than two markets in which they can participate.

The study also contributes to price discovery research with a focus on dark liquidity in several ways. First, it explores the effects inter-market fragmentation of lit and dark orders has on price discovery. It is the first study to empirically test the effects of intra-market fragmentation within the dark market in a similar fashion to which existing studies focus on intra-market fragmentation within lit exchanges. This study differentiates itself from previous works by taking into consideration that structure of the dark liquidity market itself rather than simply its market share

The study also focusses on both the local order book of the primary market as well as the global consolidated order book. Distinguishing between global and local order books allows for testing of how fragmentation impacts both retail investors and more sophisticated institutional investors. Retail investors often default to using the primary exchange (Degryse et al. (2015) and are subject to its conditions. Institutional investors have greater accessibility to multiple exchanges through the use of smart order routing technology (SORT) and can transact against the consolidated global order book.

The remainder of this section outlines the testable hypotheses contained within this study. Section 3.3.1 focuses on hypotheses relating to the informational content and trade prices and mid-quotes in lit and dark exchanges. Section 3.3.2 relates to the impact on price discovery

3.3.1 Informational Content

Zhu (2014) proposes that informed investors cluster on the heavy side of the market. Informed trades cluster together because they correlate positively with the value of the asset, and therefore, each other. As a result, informed investors face a lower probability of execution in dark pools, relative to uninformed investors. Dark pools attract less liquidity than traditional lit exchanges and therefore, can support less informed trading (Zhu, 2014; L. Ye, 2016).

Since lit exchanges offer faster execution speeds, they are more attractive to informed investors (Zhu, 2014). As dark pools proportionally attract more uninformed investors than informed investors, informed investor activity becomes more concentrated on lit exchanges. Higher concentrations of informed to uninformed activity result in improved price discovery on lit exchanges.

H3-1: Lit exchange trade prices contain more information than dark pool trade prices.

Improvements in price discovery on lit exchanges come at the cost of greater adverse selection risk and wider bid-ask spreads. Bloomfield et al. (2005) and Boulatov and George (2013) show informed investors to be sources of liquidity. Informed investors prefer to supply liquidity when adverse selection risk is high due to the informational advantage they possess. Informed investors favour supplying liquidity in highly fragmented markets in order to pick-off only the most profitable trades (Bessembinder & Kaufman, 1997; Easley et al., 1996).

H3-2A: Lit exchange mid-quotes contain more information than lit exchange trade prices.

H3-2B: The informational content of lit exchange mid-quotes is positively related to market fragmentation.

While the primary exchange is the source of the majority of permanent price adjusting information, some informed trading naturally migrates to competing lit exchanges, otherwise known as satellite exchanges (Hasbrouck, 1995). Also, informed investors use satellite exchanges to supply liquidity (Madhavan, 1995) and effectively 'cream-skim' the most profitable uninformed trades across multiple trading venues.

H3-3A: Lit exchange trade prices in the consolidated global market contain more information than lit exchange trade prices in local primary exchange.

H3-3B: Lit exchange mid-quotes in the consolidated global market contain more information than lit exchange mid-quotes in local primary exchange.

3.3.2 Intra-Market Lit Fragmentation

Intra-market lit fragmentation occurs when new exchanges operating pre-trade transparent order books are introduced into the market. Greater levels of intra-market lit fragmentation increase the informativeness of lit trade prices compared to dark trade prices. An increase in the number of trading venues with pre-trade transparency allows informed investors to conceal their intentions more easily by spreading trades across multiple exchanges (Madhavan, 1995). By using multiple lit exchanges, informed investors minimise their exposure to non-execution risk. Non-execution risk is high for informed investors in dark pools as they tend to cluster on the heavy side of the order book (Zhu, 2014).

Also, investors who can access liquidity across multiple exchanges simultaneously through the use of smart order routing technology (SORT) can offset the 'thinness' of the exchanges with price diversification benefits (Mendelson, 1987). Therefore, an increase in the level in which global exchange prices contribute to price discovery compared to trade prices originating in dark pools is expected when lit markets fragment.

However, local exchange trade prices become less informative compared to the dark exchange trade prices. As increased competitive decreases the absorptive capacity of the primary local exchange, investors look towards satellite exchanges in order to avoid adverse price changes (Pagano, 1989).

H3-4A: The informativeness of local exchange trade prices is negatively related to the level of intra-market lit fragmentation.

H3-4B: The informativeness of consolidated global exchange trade prices is positively related to the level of intra-market lit fragmentation.

3.3.3 Inter-Market Fragmentation

Both limit and market orders contain price forming information (Kaniel & Liu, 2006). Therefore, any liquidity that dark pools draw away from traditional lit exchanges will increase the informativeness of dark trade prices. This reduces the extent to which lit exchange prices contribute price forming information when compared to dark orders. However, informed investors face a lower probability of execution in dark pools, relative to uninformed investors (Zhu, 2014). Therefore, dark pools attract a higher proportion of uninformed investors than informed investors, thereby concentrating the level of informed investment on lit exchanges. Global trade prices lose less information than local trade prices as informed investors continue to use satellite exchanges to transact. Informed investors migrate to satellite markets as they provide greater execution speeds than dark pools (Zhu, 2014, L. Ye, 2016). Informed investors are also able to conceal private information better when using a fragmented network of lit exchanges versus the primary exchange.

H3-5A: There is a negative relationship between inter-market fragmentation [22] and the informativeness of lit exchange trade prices compared to dark exchange trade prices.

H3-5B: Inter-market fragmentation results in a greater concentration of informed investors, compared uninformed investors, in lit exchanges.

H3-5C: The informativeness of local trade prices is more sensitive to changes in inter-market fragmentation compared to global trade prices.

3.3.4 Intra-Market Dark Fragmentation

Informed investors continue to favour lit exchanges as fragmentation in the dark market distributes liquidity across competing dark liquidity providers and increases the non-execution risk for informed investors in any given dark pool (Zhu, 2014, L. Ye, 2016). Therefore, new dark pools must attract uninformed liquidity in order to sustain activity within the pool. This, in turn, concentrates informed investors on quoting exchanges which leads to increased adverse selection risk in the said exchanges. However, any liquidity that dark pools draw away from traditional lit exchanges will increase the informativeness of dark trade prices and decrease the informativeness of lit trade prices.

H3-6A: There is a negative relationship between intra-market dark fragmentation and the informativeness of lit exchange trade prices compared to dark exchange trade prices.

[22] Inter-market fragmentation refers to the migration of liquidity from lit exchanges to dark exchanges. See 3.2.2 for more information on inter-market fragmentation.

H3-6B: Intra-market dark fragmentation results in a greater concentration of informed investors, compared uninformed investors, in lit exchanges.

H3-6C: The informativeness of local trade prices is more sensitive to changes in inter-market fragmentation compared to global trade prices.

3.4 Data

As a result of the introduction of MiFID, Europe's stocks have fragmented across both lit and dark liquidity venues, while maintaining significant daily trading volumes across multiple venues, making them suitable for this study. This study focusses on a sample of large-cap European stocks and limits the sample to the constituents of the primary index. Millisecond time-stamped transaction-level data is collected from the Thomson Reuters Tick History Database via SIRCA. The study excludes companies that are not continuously part of the index throughout the entire observation period.

The study focusses on the top 20 listed firms in the following seven European countries, based on their membership in the major local stock index, with the final sample containing 140 stocks. The seven countries are as follows: Austria, Belgium, France, Germany, the Netherlands, Portugal and Spain. Transaction data is gathered for each stock and consists of transactions from the dark and lit liquidity providers indicated in Table 3-1.

The study period is 1 November 2008 to October 31 2016. This time frame is ideal as it consists of three very distinct periods of fragmentation within European equity markets: i) *Intro to MiFID (November 1 2008 to October 31 2011) ii)* Post-Intro to MiFID *– (November 1 2011 to October 31 2013) iii)* MiFID Maturity*– (November 1 2013 to October 31 2016).*

The study improves upon previous research (Comerton-Forde & Putniņš, 2015; Gresse, 2017; Hatheway et al., 2017) by allowing for a greater geographic distribution within the sample across a longer timeframe. MiFID has aided in removing geographical barriers within the European trading market thus creating the need for a study that spans multiple countries and views the pan-European market as a virtual market with multiple entry points (O'Hara and Ye, 2011).

Table 3-1: Exchange List

Exchange List	
Lit	**Dark**
Primary	Blink
Frankfurt Stock Exchange	BlockMatch
Euronext (Amsterdam, Brussels, Lisbon, Paris)	BATS Dark
	CHI-X Dark
Madrid Stock Exchange	RWB
Vienna Stock Exchange	Instinet
	Liquidnet
Satellite	NASDAQ OMX
BATS	NYFX Millenium
Chi-X	Plus Markets
Equiduct	SmartPool
NYSE ARCA	Sigma-X
Instinet	Turqiouise
NASDAQ OMX	Virt-X
Plus Markets	Posit
Quote MTF	XUBS
Turquoise	

Note. This table contains a list of the stock exchanges used in the study. Primary exchanges are the national quoting exchanges where stocks are originally listed. Other exchanges are quoting MTFs and represent satellite exchanges. Dark exchanges refer to dark pools.

3.4.1 Transaction Data

In order to calculate the various dependent and independent variables, this study sources transaction level data for each stock, across all relevant trading venues, found in Table 3-1. For equity data it should be noted, however, that transaction data cannot be collected for each dark liquidity provider as some venues submit their orders to the consolidated tape and fail to provide information regarding the exchange from which the transaction originated. The following information is required for each transaction:

1. *Stock Traded (RIC)* – An identifier that indicates which stock is traded
2. *Date* – The date of the transaction
3. *Time* – The time of the transaction (accurate to the nearest millisecond)
4. *Exchange* - The exchange from which the transaction originates
5. *Price* – The price per unit
6. *Quantity* –The number of units in the transaction

7. *Qualifier* – An identifier that supplies some additional information about the transaction (for example, ‘K’ for dark pool trades)

3.4.2 Quote Data

The following information is collected for each order book:

1. *Asset* - An identifier that indicates the stock to which the quote pertains
2. *Date* – The date of the current order book snapshot
3. *Time* – The time of the current order book snapshot
4. *Exchange* – The exchange that advertises the quotes
5. *Bid Price* – The price at which investors can sell the stock
6. *Bid Quantity* – The number of units available at the current bid price
7. *Bid Number of Investors* – the number of investors at the current bid price
8. *Ask Price* – The price at which investors can purchase the stock
9. *Ask Quantity* – The number of units available at the current ask price
10. *Ask Number of Investors* – The number of investors at the current ask price

3.5 Methodology

This section introduces the methods used to conduct the study. Independent and dependant variables are calculated using a combination of SAS, Excel and custom C++ code. SPSS is used to perform the final regression analysis. The following subsections provide further detail regarding the variables and regression analyses used to test the hypothesis outlined in section 3.3. Section 3.5.1 introduces the methods used to calculate price discovery, the dependant variable. Section 3.5.2 discusses independent variables. Section 3.5.3 discusses the regression models used to test the hypotheses. Section 3.5.4 tests the regression assumptions to ensure the validity of the regression results.

3.5.1 Measuring Price Discovery

In line with previous research, including those focussing on the implications of the increased use of dark liquidity (Comerton-Forde & Putniņš, 2015), we measure price discovery using Hasbrouck’s (1995) information share (IS) and Gonzalo and Granger’s (1995) component share (CS). These two measures are considered to be the quintessential measures of price discovery between two price series. They both rely on distinguishing between two components of changing prices: the permanent components, which imply changes in the fundamental value of the asset, and temporary components, which represent the noise contained within price variations. The IS metric focuses on the decomposition of the variance of efficient price changes resulting from both price series while the CS metric is a convergence model which isolates for the linear combination of weights that cause the two price series to converge at the fundamental value. In a 2002 study, Baillie et al. document that IS and CS are not substitutes, but complementary measures that focus on different aspects of price discovery. They deduce that the IS metric is simply a variance-weighted version of CS. However, while IS is considered to be more effective in determining which price series contributes more towards price discovery, it is also more heavily influenced by the level of noise contained within the data (Putniņš, 2013). As a result, we use both measures in our study in order to generate a more robust conclusion. (Baillie, Booth, Tse, & Zabotina, 2002; Gonzalo & Granger, 1995; Joel Hasbrouck, 1995)

To calculate both IS and CS the study first estimates the following vector error correction model (VECM) for each stock-day using 1 second time intervals, t, and a lag input of 60:

$$\Delta p_{1,t} = \alpha_1(p_{1,t-1} - p_{2,t-1}) + \textstyle\sum_{i=1}^{60} \gamma_1 \Delta p_{1,t-i} + \sum_{j=1}^{60} \delta_1 \Delta p_{2,t-j} + \varepsilon_{1,t} \quad (1)$$

$$\Delta p_{2,t} = \alpha_2(p_{1,t-1} - p_{2,t-1}) + \sum_{i=1}^{60} \vartheta_1 \Delta p_{1,t-i} + \sum_{j=1}^{60} \varphi_1 \Delta p_{2,t-j} + \varepsilon_{2,t}$$

where p_1 and p_2 are two price series at each 1-second time interval, α is the error correction vector, and ε_t is the zero-mean vector of serially uncorrelated innovations, with covariance matrix Ω.

In line with previous studies (Comerton-Forde & Putniņš, 2015) the study calculates two versions of the VECM above to utilise within the IS and CS calculations. In the first set of measures p_1 is a series of the last available lit trade prices at each 1-second time interval and p_2 is a series of the last available dark trade prices at each 1-second time interval across all dark pools. This results in the measures IS_{LvD} and CS_{LvD} which allows the study to determine the extent to which lit market transactions contribute to price discovery when compared to dark pool transactions. In the second set of measures, p_1 is a series of the last available lit trade prices at each 1-second time interval, and p_2 is a series of lit mid-quotes at each 1-second time interval. The resulting measures, IS_{LvM} and CS_{LvM}, allow the study to investigate the contribution that trade prices resulting from exchanges with displayed order books make towards price discovery when compared to the best quotes from said exchanges.

Hasbrouck's (1995) IS defines the information share of a market as the proportion of variance of a common factor that are attributed to innovations in the market. It is calculated as follows:

$$IS_j = \frac{\psi_j^2 \sigma_j^2}{\psi \Omega \psi'} \tag{2}$$

where ψ is the common row vector such that ψe_t is the amount of the price change that is permanently adjusted into the price as a result of the release of new information, e_t is a zero-mean vector of serially uncorrelated innovations with covariance matrix $\Omega,$ and σ_j^2 is the variance of price series j.

The study continues with Hasbrouck's (1995) method, as outlined by Baillie et al. (2002) and turn the more generalized version of Equation (1) into a vector moving average:

$$\Delta p_t = \Psi(L)\varepsilon_t \tag{3}$$

and then integrate:

$$P_t = \Psi(1)\sum_{i=1}^{t} \varepsilon_i + \Psi^*(L)\varepsilon_t \ , \tag{4}$$

where $P_t = (p_{1,t}, p_{2,t})'$, $\Psi(L)$ and $\Psi^*(L)$ are matrix polynomials in the lag operator (L), and $\Psi(1)$ is the sum of the moving average coefficients and is referred to as the impact matrix.

Finally, Hasbrouck (1995) states that if the rows of the long-run impact matrix, $\Psi(1)\varepsilon_t$, are identical then the long-run impact should be the same for all prices. Therefore, if the study defines $\psi = (\psi_1, \psi_2)$ as the common row vector in $\Psi(1)$ and transform Equation 4 into:

$$P_t = \iota\psi(\textstyle\sum_{i=1}^{t} \varepsilon_i) + \Psi^*(L)\varepsilon_t \tag{5}$$

where ι is a column vector of 1s.

Gonzalo and Granger's (1995) component share decomposes the permanent price change into a combination of two prices. The study uses Equation 4 from above and defines the permanent price change (common factor), f_t, to be:

$$f_t = \Gamma P_t \tag{6}$$

where Γ is the common factor coefficient vector.

The study follows the approach of Degryse et al. (2015) and Gresse (2017) and distinguishes between global and local order books.[23] The Thomson Reuters Tick History database provides information on transactions as well as the best bid and ask quotes and is accurate up to the nearest millisecond. Raw transactional and order book data is processed using custom C++ code in order to match prices as indicated by lit transactions, dark transactions, and order book midquotes. SAS is used to process the transaction and quote data in order generate the price discovery measures outlined in this section.

3.5.2 Independent Variables

This following section lists the series of independent variables used in the study. It begins by outlining the key regressors relating to fragmentation which are used to test the hypotheses. Finally, this section is concluded with a description of the control variables. Similar to the price discovery variables previously mentioned, the independent variables in this section are calculated from Thomson Reuters Tick History data using custom C++ code with some additions being performed in Excel.

3.5.2.1 Fragmentation Measures

This section discusses the methods used to test the impact of fragmentation on the price discovery process. The study separates equity exchanges into two distinct pools depending on their levels of pre-trade transparency: lit exchanges are those that offer pre-trade transparency by publicly displaying their order books while dark exchanges offer no pre-trade transparency. Fragmentation is ultimately a measure of competition and the study is interested in the ways in which these markets face competition, both amongst themselves and with each other.

The study begins by measuring the level of competition among lit exchanges resulting from the migration of trades from one lit exchange to another. Lit fragmentation results from the proliferation of MTFs due to the policy changes that MiFID introduced. The study refers to this as intra-market lit fragmentation. Following previous research (Buti et al., 2017; Degryse et al., 2015; Gresse, 2017) the study employs the Herfindahl-Hirschman Index (HHI) to measure the extent to which trading activity concentrates around a single trading venue. As a result, the measure of lit fragmentation for stock i at time t ($LF_{i,t}$) is as follows:

[23] For global trade prices in lit exchanges we sort transactions chronologically and reference the resulting consolidated trade reports. We follow a similar approach for dark pool price series data and do not foresee any problems given that dark pool prices are pegged to the midpoint of either the primary exchange for a given stock or the global consolidated market.

$$LF_{i,t} = 1 - \sum_{v=1}^{n} MS_{i,t,v}^{2} \quad (7)$$

where i represents a particular company,

t is the observation day,

v represents a particular visible liquidity venue,

MS_v^2 is the squared market share of lit trading venue v, measured by the number of stocks traded in venue v when compared to the lit market as a whole.

The study uses 1-HHI to allow the measure to more intuitively measure fragmentation. An increase in *LF* corresponds to increased fragmentation in the market for any particular stock.

The next measure focuses on the competition between quoting and non-quoting exchanges. Due to the increasing popularity of dark pools the equity market is no longer consolidated around exchanges that offer pre-trade transparency. The study refers to the migration of transactional volume from lit to dark exchanges as inter-market fragmentation. In line with previous studies (Buti et al., 2017; Comerton-Forde & Putniņš, 2015; Degryse et al., 2015; Gresse, 2017) we measure the level of competition/fragmentation between quoting and non-quoting exchanges as the market share of dark trades (*DMS*).

$$DMS_{i,t} = DV_{i,t} / Vol_{i,t} \quad (8)$$

where i represents a particular company,

t is the observation day,

$DV_{i,t}$ is the daily transaction volume, in Euro, of the dark order book market,

$Vol_{i,t}$ is the total daily volume for the firm, in Euro.

This variable is used to compliment the dark volume measure as it informs us whether the increased volume in the dark market is a result of increased total volume[24] or trade migrations from the lit to the dark market.[25]

Finally, the measure of the level of fragmentation, that is, the degree of competition, in the dark pool market employed in this study is similar to the one for lit fragmentation (LF). However, this time the focuses exclusively on the market share of trading venues that do not offer pre-trade transparency. This is referred to as intra-market dark fragmentation as it measures the extent to which dark pools compete with each other.

[24] The increase in dark volume could be a direct result of an increase in total trading activity for the day.

[25] As an increase in dark volume coupled with an increase in the proportion of dark trading implies that subsequent effects are as a result of trades favouring execution in the dark market over the lit market.

$$DF_{i,t} = 1 - HHI_{i,t} = 1 - \sum_{v=1}^{n} MS_{i,t,v}^2 \quad (9)$$

where i represents a particular company,

t is the observation day,

v represents a particular dark liquidity venue,

MS_v^2 is the squared market share of dark trading venue v, measured by the number of stocks traded in venue v when compared to the dark market as a whole.

Previous dark pool price discovery studies focus exclusively on the market share of dark pools. That is the extent to which they compete with traditional quoting exchanges. However, in this study, competition is measured within the dark market itself, just as we have done with the lit market. Only one previous study (Majtyka et al., 2015) measures the level of intra-market dark fragmentation; however, the authors focus on liquidity measures as opposed to price discovery when analysing its impact.

3.5.2.2 Control Variables

The regressions control for the following factors: volatility, bid-ask spread, market capitalisation and total daily volume. The following details the construction of the control variables used for the study:

1. **Volatility $(\sigma)_{i,t}$** - The volatility of an asset is measured by its standard deviation of returns over the course of a trading day, calculated as follows:

i. $$r_{i,t,s} = Ln\left(\frac{Mi_{,t,s}}{M_{i,t-1},s}\right) \quad (10)$$

where i represents a particular asset,

t is the observation day,

s is the second/time of day t,

$r_{i,t,s}$ is the logarithmic return between 1-second snapshots,

$Mi_{,t,s}$ is the current midpoint of the best bid-ask spread,

$M_{i,t-1}, s$ is the midpoint of the best bid-ask spread from the previous second.

ii. $$\overline{r_{i,t}} = \frac{\sum_{s=1}^{S} r_{i,t,s}}{S} \quad (11)$$

where *i* represents a particular asset,

t is the observation day,

s is the second/time of day t,

$r_{i,t,s}$ is the logarithmic return between 1-second snapshots,

$\overline{r_{i,t}}$ is the average return over the course of the trading day,

S is the number of seconds over the course of the trading day.

iii. $\sigma_{i,t} = \sqrt{\frac{\sum_{s=1}^{S}(r_{i,t,s}\_\ \overline{r_{i,t}})^2}{S-1}}$ [26] (12)

where *i* represents a particular asset,

t is the observation day,

s is the second/time of day t,

$r_{i,t,s}$ is the logarithmic return between 1-second snapshots,

$\overline{r_{i,t}}$ is the average return over the course of the trading day,

S is the number of seconds over the course of the trading day.

2. **Bid-Ask Spread (BASp)$_{\mathbf{i,t}}$** – Average quoted spread for exchange *i* over the course of a trading day, *t*. It is calculated as follows:

i. $QS_{i,t,s} = \frac{P_{i,t,s}{}^{BestAsk} - P_{i,t,s}{}^{BestBid}}{P_{i,t,s}{}^{BestAsk}}$ (13)

where *i* represents a particular company,

t is the observation day,

s is the second/time of day t.

$P_{i,t,s}{}^{BestAsk}$ is the best available ask price,

$P_{i,t,s}{}^{BestBid}$ is the best available bid price.

The bid-ask spread is calculated throughout each second of the day and averaged over the course of a trading day.

[26] S-1 is used as this is a sample measure because it is not possible to have all possible outcomes.

3. **Market Capitalisation $(MC)_{i,t}$ -** Market capitalisation is the size of the company and is calculated as follows:

   i. $MC_{i,t} = Pr_{i,t} * NumSh_{i,t}$ (14)

   where $NumSh_{i,t}$ is the total number of shares outstanding.[27]

4. **Total Volume $(Vol)_{i,t}$** – Total volume is the total trading volume of stock *i* over the course of a single trading day, *t*, measured in Euro(€).[28] It is calculated as follows:

   i. $Vol_{i,t} = \sum_{r=1}^{N} NumShares_{r,i,t} * Price_{r,i,t}$ (15)

   where *i* represents a particular company,

   t is the observation day,

   r is the current transaction,

   N is the total number of transactions over the course of trading day *t,*

   $NumShares_{r,i,t}$ is the number of shares in transaction *r*,

   $Price_{r,i,t}$ is the price at which transaction r took place.

3.5.3 Panel Regression

The data is analysed using panel regression performed in SPSS. This type of regression is appropriate as the data consists of multiple entities (stocks) that are observed over more than two points in time. A time series analysis would not be appropriate here as the data consists of multiple entities (stocks). Also, a cross sectional regression would not be appropriate as the data consists of observations over multiple time periods.

The base for the regression formula is:

$$L_{i,t} = b_0 + b_1LF_{i,t} + b_2DMS_{i,t} + b_3DF_{i,t} + b_4\sigma_{i,t} + b_5lnBASp_{i,t} + b_6lnMC_{i,t} + b_7lnVol_{i,t} + \mu_{i,t} \quad (16)$$

[27] To determine how many shares a company has outstanding at any given point in time we used the figures as presented in quarterly reports.
[28] For control variables 2-4 we use the LN() of the original value. Logarithms convert changes in variables into percentage changes and this figure will provide a more descriptive result as it will scale down the changes amongst stocks.

where *LF*, *DMS*, and *DF* refer to the aforementioned measures of fragmentation and the remainder refer to control variables for volatility (σ), bid-ask spread (*BASp*), market capitalization (*MC*), and total volume (*Vol*).

The regression model is extended to include the entity and time fixed effects. The extended model is as follows:

$$L_{i,t} = \alpha_i + \gamma_t + b_1 LF_{i,t} + \ b_2 DMS_{i,t} + \ b_3 DF_{i,t} + \ b_4 \sigma_{i,t} + b_5 lnBASp_{i,t} + b_6 lnMC_{i,t} + b_7 lnVol_{i,t} + \mu_{i,t} \ . \tag{17}$$

3.5.3.1 Entity Fixed Effects

It is important that the model controls for omitted variables in the panel data when the omitted variables vary across entities but do not change over time. These include factors such as the industry in which the company operates as well as its organisational structure. To account for this effect in the model a set of binary dummy variables, $D_2, D_3 .. D_n$, are added where D_i is a fixed effect binary dummy variable for stock *i* that does not change over time. This results in the following regression model:

$$L_{i,t} = b_0 + \ b_1 LF_{i,t} + \ b_2 DMS_{i,t} + \ b_3 DF_{i,t} + \ b_4 \sigma_{i,t} + b_5 lnBASp_{i,t} + b_6 lnMC_{i,t} + b_7 lnVol_{i,t} + b_8 D_2 + b_9 D_3 + \cdots + b_{7+n-1} D_n + \mu_{i,t} \tag{18}$$

where $D_2, D_3 .. D_n$ are the fixed effect binary dummy variables for stock *i* which are set to 1 when the data pertains to stock *i*, and 0 otherwise. The resulting model consists of n intercepts, 1 for each observed entity (stock). The following specification is used in the regression:

$$L_{i,t} = b_0 + \ b_1 LF_{i,t} + \ b_2 DMS_{i,t} + \ b_3 DF_{i,t} + \ b_4 \sigma_{i,t} + b_5 lnBASp_{i,t} + b_6 lnMC_{i,t} + b_7 lnVol_{i,t} + \ b_8 Z_i + \ \mu_{i,t} \tag{19}$$

where Z_i is the unobserved variable which varies from stock to stock but remains fixed over time. This can be simplified to:

$$L_{i,t} = \alpha_i + \ b_1 LF_{i,t} + \ b_2 DMS_{i,t} + \ b_3 DF_{i,t} + \ b_4 \sigma_{i,t} + b_5 lnBASp_{i,t} + b_6 lnMC_{i,t} + b_7 lnVol_{i,t} + \ b_8 Z_i + \ \mu_{i,t} \tag{20}$$

where $\alpha_i = b_0 + b_8 Z_i$.

The former model, contained in Equation 18 , define the change in the y-intercept with respect to the intercept of the first stock in the study[29], stock 1, while the latter models, contained in Equations 19 and 20, reorganise the inputs and define a unique intercept for each stock.

3.5.3.2 Time Fixed Effects

Just as entity fixed effects control for variables that are constant over time but differ across entities, time fixed effects control for variables that are constant across entities but change over time. This is particularly important over the observed period as effects resulting from events such as the Global Financial Crisis (GFC) are difficult to measure but must be accounted for. To account for this effect, we add to the model a set of binary dummy variables, $S_2, S_3 .. S_n$, where S_t is a quarterly fixed effect binary dummy variable for time *t* that remains constant across entities but changes over time. This results in the following regression model:

$$L_{i,t} = b_0 + b_1 LF_{i,t} + b_2 DMS_{i,t} + b_3 DF_{i,t} + b_5 \sigma_{i,t} + b_6 lnBASp_{i,t} + b_7 lnMC_{i,t} + b_8 lnVol_{i,t} + b_9 D_2 + b_{10} D_3 + \cdots + b_{8+n-1} D_n + b_{8+n} S_2 + b_{8+n+1} S_3 + \cdots + b_{8+n+T-2} S_n + \mu_{i,t} \quad (21)$$

where $S_2, S_3 .. S_n$ are the fixed effect binary dummy variable for time t which are set to 1 when the data pertains to period t, and 0 otherwise.

3.5.4 Regression assumptions

For the panel regression results to be valid, they must first adhere to the assumptions of linear regression. The true relationship between independent and dependent variables is distorted if the assumptions are not met. As a result, regression coefficients lose their interpretability. The remainder of this section tests for the presence of the following: normality, linearity, homoscedasticity and multicollinearity. Tables and figures in this section report on only a subset of the variable and regression combinations examined in this study. Omitted results do not deviate from the reported values and are considered redundant for reporting purposes.

3.5.4.1 Normality

Linear regression assumes that residuals of the dependent variables are normally distributed. Regression coefficients and significant testing are distorted when residuals are not normally

[29] Note that there is no D_1 but only $D_2 .. D_n$

distributed. This study runs normality tests on both the individual variables as well as the resulting model itself.

Panel A: ***IS_{LvD}*** ***Panel B:*** ***CS_{LvD}***

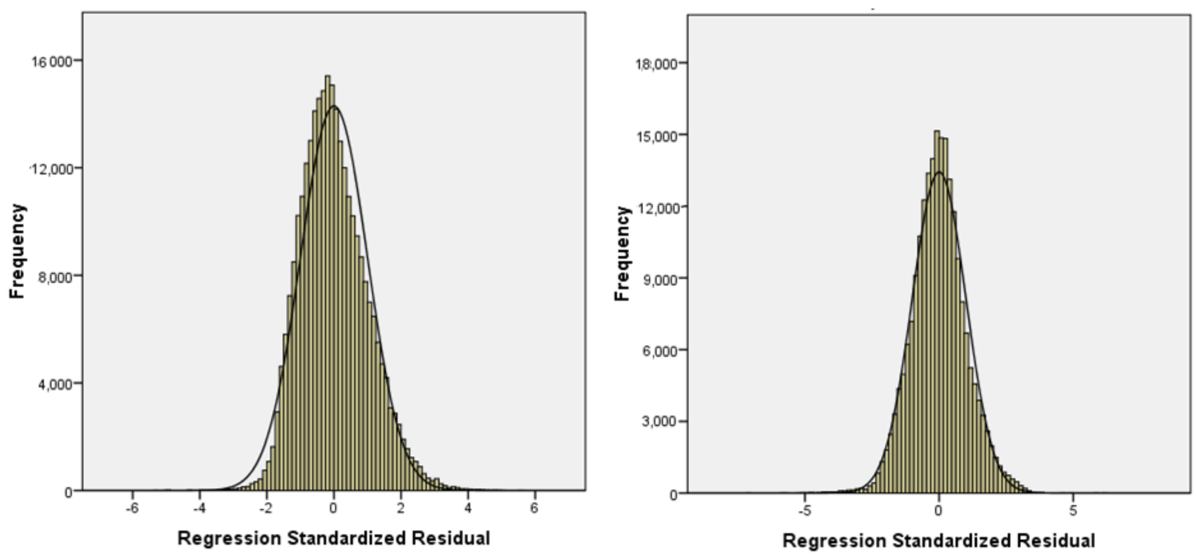


Figure 3-4: Distribution of Dependent Variable Residuals

Note. The figure displays the distribution of dependent variable residuals resulting from regression analyses. The results originate from OLS regressions on variables IS_{LvD} and $CS_{LvD,}$ located in Panels A and B, respectively. The regression included stock and time fixed effects and consists of local market measures.

The analysis begins by graphing residuals for each independent variable and inspecting them to see whether a normal distribution is present. Figure 3-4 displays the distribution of residuals for the following dependent variables: IS_{LvD} and CS_{LvD}. The results stem from panel regressions using local measures of IS_{LvD} and CS_{LvD} with both time and stock fixed effects. The results presented in Panels A and B of Figure 3-4 indicate that the residuals do not extensively deviate from the normal distribution, as indicated by the fitted line. These results support the assumption of normality.

The normal probability plots in Figure 3-5 provide further support for the normality assumption. While slightly bowed, Panels A and B follow along fitted line reasonably well. Therefore, the tests performed in this section support the normality assumption.

Panel A: IS_{LvD} ***Panel B: CS_{LvD}***

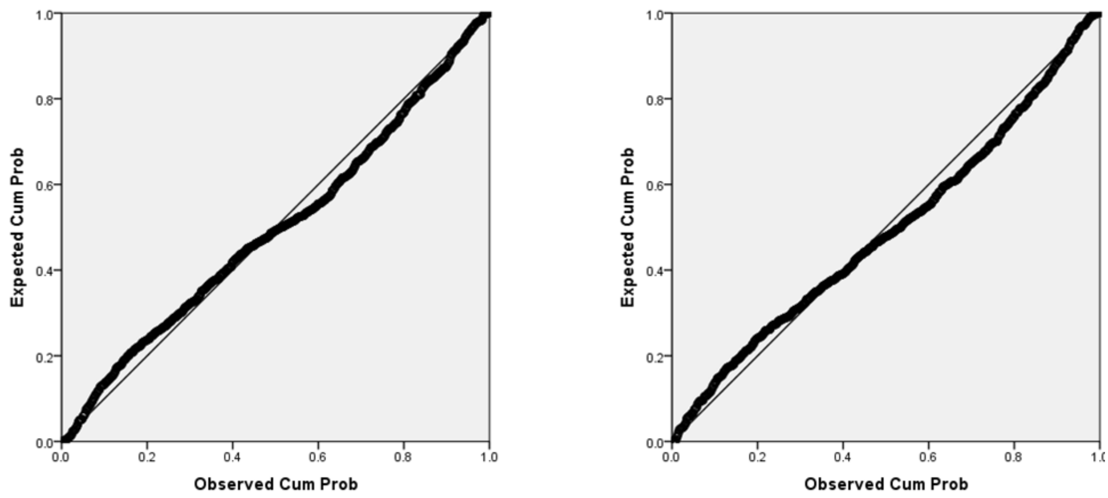


Figure 3-5: Normal Probability Plots

Note. The figure displays normal probability plots. The results are collected from performing an OLS regression on variables IS_{LvD} and CS_{LvD} located in Panels A and B, respectively. The regression included stock and time fixed effects and consists of local market measures.

3.5.4.2 Linearity

Next the study examines the linearity of the relationship between independent and dependent variables. Deviations from linearity result in meaningless coefficients as the model attempts to explain a non-linear relationship using linear variables. Tests for linearity entail plotting the regression residuals against predicted values. A non-linear relationship exists if the variance of the residuals changes significantly along with changes in the predicted value.

Panel A: IS_{LvD} ***Panel B: CS_{LvD}***

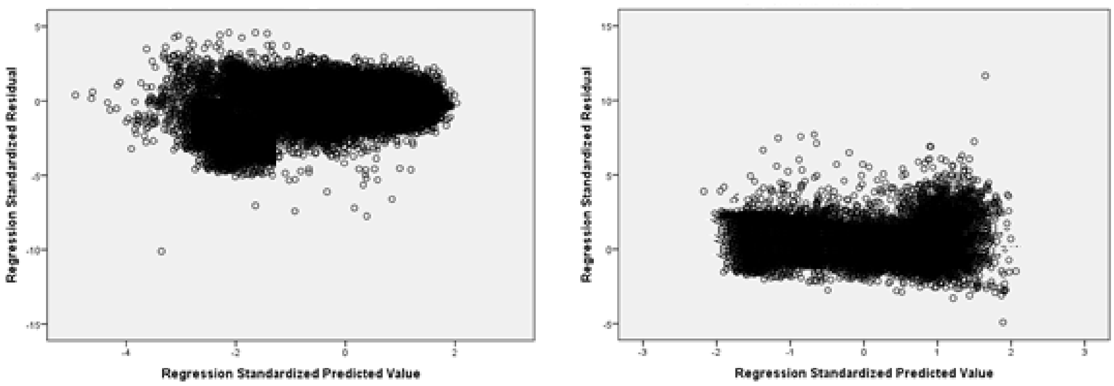


Figure 3-6: Standardised Residuals versus Predicted Values

Note. This figure plots the standardised residuals and predicted values. The results are collected from performing an OLS regression on variables IS_{LvD} and CS_{LvD} located in Panels A and B, respectively. The regression included stock and time fixed effects and consists of local market measures.

Figure 3-6 displays the standardised residual versus predicted value plots for IS and CS measures in Panels A and B, respectively. Both panels convey that a linear relationship exists as there is no noticeable pattern of deviation in the plotted values supporting the linearity assumption.

3.5.4.3 Homoscedasticity

Homoscedasticity occurs when the variance of the residuals remains constant across all predicted values. That is, var($\mu_{i,t} | X_i$ = x), is constant for i = 1…n. Patterns in the standardised residual versus predicted values indicate that the term is heteroskedastic. Linear regression models are unable to generate meaningful coefficients from heteroscedastic data. As reported in Section 3.5.4.2, both Panels of Figure 3-6 show that the variance in the residual terms is reasonably constant across all predicted value. Therefore, the assumption of homoscedasticity is supported.

3.5.4.4 Multicollinearity

Testing for multicollinearity among the independent variables is the final assumption test in this study. High levels of multicollinearity in the data imply that there are some redundant variables. When the correlation coefficient between two variables is high, they will attempt to explain the same changes in the dependent variable if used together. Like in previous assumption tests, violations of independence, that is, high levels of multicollinearity, result in less meaningful regression coefficients.

Table 3-2 contains the correlation measures between all independent measures. This table shows that there is some level of multicollinearity between the three fragmentation measures: LF, DMS and DF. Correlation coefficients among pairs of fragmentation measures range from 0.49 to 0.59. This means that the fragmentation measures are at least moderately correlated. Bid-ask spread (BASp) is also moderately negatively correlated with lit fragmentation (LF), market capitalisation (MS) and total volume (Vol).

Table 3-2: Correlations

	LF	DMS_{DP}	DF_{DP}	σ	BASp	MC	Vol
LF	1.00						
DMS_{DP}	0.49	1.00					
DF_{DP}	0.59	0.54	1.00				
σ	0.19	0.11	0.24	1.00			
BASp	-0.40	0.11	-0.03	0.34	1.00		
MC	-0.02	0.09	0.06	-0.09	-0.64	1.00	
Vol	0.13	0.19	0.09	0.03	-0.49	0.51	1.00

Note. This table shows the correlation coefficients between the independent variables contained within the study. All measures have been compared in a local context. LF denotes the fragmentation of lit exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DMS measures the market share of off-order book transactions. DF denotes the fragmentation of dark exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). The DMS_{DP} and DF_{DP} measures of fragmentation consist exclusively of transactions that original from dark pools. σ is the standard deviation of 1-minute mid-quote returns as measured in basis points. BASp is the average bid-ask spread at the best price level and is weighted by the total depth at that price level. MC is the market capitalisation and is measured by the number of outstanding shares multiplied by the average daily price and is weighted by the total volume transacted at each price. Vol is the total volume and consists of the value of shares transacted in the stock over a given stock day and is measured in Euros (€). Vol includes lit and dark transactions, including those originating from dark pool and over-the-counter trades.

The variance inflation factor (VIF) also tests for the presence of multicollinearity among the variables in the model. The test entails regressing one independent variable against the others. The process repeats until all independent variables have been regressed against. VIF values below three indicate that multicollinearity is at a minimum. VIF values between three and five indicate a moderate level of multicollinearity. VIF values over 5 and 10 indicate significant and high multicollinearity, respectively.

Table 3-3: Variance Inflation Factors

Panel A: LF

	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
DMS	0.198	5.06
DF	0.333	3
LN Volatility	0.175	5.7
LN Spread	0.154	6.49
LN Mcap	0.225	4.45
LN Total Vol	0.17	5.87

Panel B: DMS

	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
LF	0.331	3.02
DF	0.146	6.861
LN Volatility	0.421	2.374
LN Spread	0.212	4.724
LN Mcap	0.126	7.966
LN Total Vol	0.156	6.417

Note. This table contains information on the variance inflation factors (VIF). The results are collected from performing an OLS regression on the previously dependent variables LF and DMS located in Panels A and B, respectively. The regression included stock and time fixed effects and consists of local market measures. Note that dummy variable VIF values are excluded from the table.

Table 3-3 contains the VIF resulting from regressions performs on LF and DMS in Panels A and B, respectively. The results indicate the presence of moderate levels of multicollinearity in most variables. This needs to be noted when interpreting the coefficient estimates in the followings main results section.

3.6 Results

This section presents the results of the analysis on fragmentation and its impact on the informativeness of exchange trades versus dark pool trades as well as exchange trades and exchange quotes. The section starts by reviewing key descriptive statistics then moves to hypothesis testing and discussion.

3.6.1 Descriptive Statistics

Descriptive statistics regarding the key fragmentation measures are reported in Table 3-4. The dark pool market appears to be more fragmented than the competing lit market with DF_{DP} and LF figures of 0.711 and 0.588, respectively. Taking into account all off order book transactions, dark liquidity is even more fragmented with a DF_{DP} of 0.751 which can be attributed to the over-the-counter transactions being reported to both the primary exchange and competing MTFs. On average, dark pools account for 9.74% of all trading activity within the sample period while all off order book transactions account for 28.31%. This indicates that traditional forms of dark liquidity remain more popular that fully-automated dark pools. One reason this may occur is that upstairs brokers may be able to tap into unexpressed liquidity of larger institutional traders, thereby expanding the overall amount of liquidity that is available to the market (Grossman, 1992).

Table 3-4: Fragmentation Measures

	Mean	Std. Dev.	Q1	Q2	Q3
Lit Fragmentation					
LF	0.588	0.074	0.569	0.604	0.649
Dark Market Share					
DMS_{DP}	0.097	0.046	0.053	0.088	0.119
DMS_{A}	0.283	0.104	0.153	0.263	0.297
Dark Fragmentation					
DF_{DP}	0.695	0.048	0.631	0.674	0.705
DF_{A}	0.751	0.058	0.711	0.750	0.793

Note. This table contains the means, standard deviations, and medians (Q2) as well as the first (Q1) and third (Q3) quartiles of various price discovery measures. LF denotes the fragmentation of lit exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DF denotes the fragmentation of dark exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DF_{DP} consists of trades that originate exclusively from dark pools while DF_{A} consists of all off-order book transactions. DMS measures the market share of off-order book transactions. DMS_{DP} consists of trades that originate exclusively from dark pools while DMS_{A} consists of all off-order book transactions.

Figure 3-7 presents the levels of fragmentation both with and without over-the-counter and other non-dark pool transactions, DFA and DPDP, respectively versus the lit market level of fragmentation. This data is for the FTSE-100 stocks and shows that the lit market is consistently less fragmented than the dark pools.

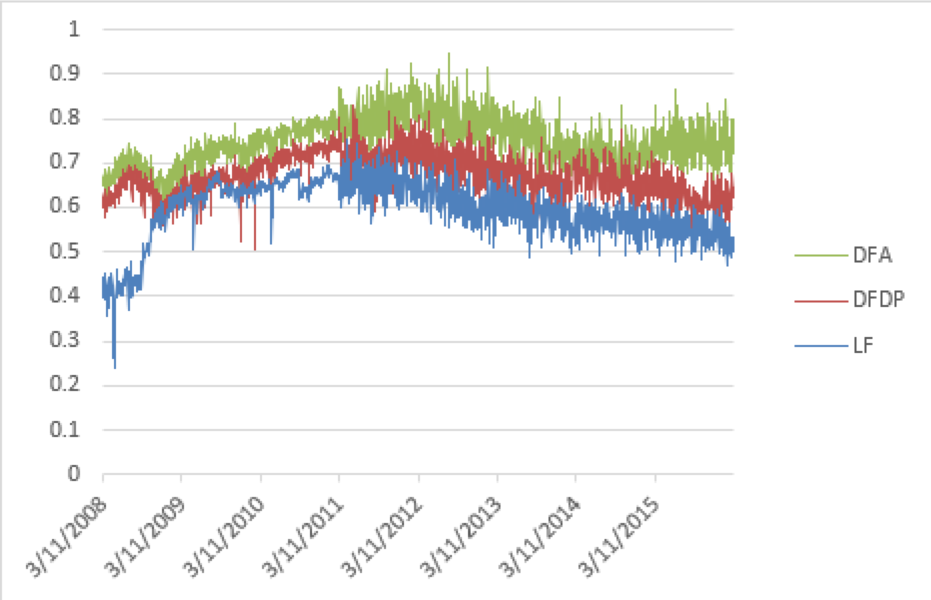


Figure 3-7: Intra-Market Fragmentation (Lit and Dark)

Note. The figure shows that average daily level of fragmentation per company in both lit (LF) and dark (DF) markets as measured by the (1- Herfindahl-Hirschman Index). The figure presents levels of fragmentation both with and without over-the-counter and other non-dark pool transactions, DF_A and DP_{DP}, respectively. Values close to 0 indicate that the market is highly concentrated while values close to 1 indicate that the market is highly fragmented, with 0 indicating perfect consolidations while 1 indicating perfect fragmentation. The labels in the legend appear vertically in the same order as the lines in the graph.

Some key descriptive statistics are reported in Table 3-5. The average market capitalization for firms in the study is roughly €25.6 billion, however this is largely due to the skewness of the data and the presence of several large firms. The median firm size is approximately €17.9 billion with 25% of firms being worth no more than €5.7 billion. Total daily volume per stock averages to €67 million per day, though these results are quite volatile. Average spreads over the sample period are also observed to be 109.2 basis points (bps) with a mean of 58.3 bps.

The analysis of the migration of price forming information is first focused on exchanges offering pre-trade transparency compete with each other for liquidity (intra-market lit fragmentation). Next, the study moves to the effect of competition resulting from the migration of liquidity between exchanges offering different levels of pre-trade transparency (inter-market fragmentation). The analysis then shifts to the effect of competition within the dark pool market (intra-market dark fragmentation). Finally, we perform several robustness tests. Note that until we reach the robustness test, the study focuses on dark liquidity that exclusively comes from dark pools and excludes all other off-order book transactions.

Table 3-5: Descriptive Statistics

	Mean	Std. Dev.	P25	Median	P75
σ (bps)	25.1	19.4	15.4	21.8	31.6
BASp (bps)	109.2	154.8	28.6	58.3	163.5
MC (millions of EUR)	25,586	29,390	5,696	17,904	33,376
Vol (thousands of EUR)	67,017	74,394	11,494	49,140	93,337

Note. This table contains the means, standard deviations, and medians (Q2) as well as the first (Q1) and third (Q3) quartiles of various price discovery measures. Values are calculated over a single stock day on the primary market of exchange. σ is the standard deviation of 1-minute mid-quote returns as measured in basis points. BASp is the average bid-ask spread at the best price level and is weighted by the total depth at that price level. MC is the market capitalisation and is measured by the number of outstanding shares multiplied by the average daily price and is weighted by the total volume transacted at each price. Vol is the total volume consists of the value of shares transacted in the stock over a given stock day and is measured in Euros (€). Vol includes lit and dark transactions, including those originating from dark pool and over-the-counter trades.

3.6.2 Price Discovery

The first hypothesis (H3-1) states that lit exchange trade prices contain more information than dark pool trade prices. The results for the test of H3-1 are reported in Table 3-6 which shows the price discovery shares for lit market prices compared to dark market prices as measured by IS_{LvD} and CS_{LvD}. Both local and global IS_{LvD} and CS_{LvD} measures are reported in order to differentiate between the informativeness of trades transacted on the primary exchange as opposed to those of the greater consolidated market. The results are consistent with other studies in that they support H3-1 that the majority of information results from trades in the visible order market as opposed to the dark market, with IS_{LvD} and CS_{LvD} figures of 81.35% and 83.88%, respectively. In the context of a consolidated global market, the IS_{LvD} and CS_{LvD} figures increase to 85.77% and 89.59%, respectively. The higher result for the global market supports H3-3b that lit exchange trade prices in the consolidated global market contain more information than lit exchange trade prices in local primary exchange. These results indicate that the overall market for a stock consisting of many exchanges provides greater information, when compared to dark transactions, than a single primary market. Global consolidated figures encapsulate the entirety of lit market trades and are more likely to include greater representation from informed traders as they represent the actions of all those who trade in a specific stock rather than a particular subset of investors.

Table 3-6: Price Discovery Measures

	Mean	Std. Dev.	Q1	Q2	Q3
Local					
IS_{LvD}	0.814	0.068	0.786	0.830	0.851
CS_{LvD}	0.839	0.074	0.800	0.826	0.858
IS_{LvM}	0.417	0.125	0.353	0.386	0.481
CS_{LvM}	0.455	0.136	0.380	0.409	0.508
Global					
IS_{LvD}	0.858	0.076	0.840	0.934	0.964
CS_{LvD}	0.896	0.077	0.862	0.902	0.923
IS_{LvM}	0.386	0.118	0.338	0.362	0.462
CS_{LvM}	0.434	0.091	0.351	0.401	0.482

Note. This table contains the means, standard deviations, and medians (Q2) as well as the first (Q1) and third (Q3) quartiles of various price discovery measures. Individual values are calculated over a single stock day and cover both the local primary exchanges as well as the global consolidated results. IS_{LvD} and CS_{LvD} are the information and component shares, respectively, for lit trade prices as compared to dark trade prices. IS_{LvM} and CS_{LvM} are the information and component shares, respectively, for lit market mid-quote as compared to dark trade prices.

The results are also supported by the individual country IS_{LvD} and CS_{LvD} measures. Again the finding is that all countries included in the study produce mean IS_{LvD} and CS_{LvD} results of at least 68%. However, countries with lower daily transactional volume such as Austria, Belgium, and Portugal present lower bounds near the 50% range, while the remaining markets experience more stability in the variability of the lit market price information factors. This change is justified by the fact that smaller transacted stocks tend to have wider relative bid-ask spreads and as a result encourage transaction in the dark market by informed investors

(Zhu, 2014). Tight upper and lower bounds are to be expected due to the frequency of the data. By using granular second time intervals significant deviation from the mean/median result is not expected.

Hypothesis H3-2A states that lit exchange mid-quotes contain more information than lit exchange trade prices. The results in Table 3-6, lines 3 and 4, test the contribution of lit market quotes towards the price discovery process when compared to lit transaction prices. The results show that local IS_{LvM} and CS_{LvM} measurements average approximately 41.65% and 45.46% over the study period, respectively. These figures show that lit quotes contribute more towards price discovery when compared to lit transaction prices. This is expected as studies including Bloomfield et al. (2005) and Boulatov and George (2013) find informed investors to be sources of liquidity.

In relation to global markets, hypothesis H3-3B states that lit exchange mid-quotes in the consolidated global market are expected to contain more information than lit exchange mid-quotes in local primary exchange. The results in lines 7 and 8 of Table 3-6 indicate that the informativeness of trade prices compared to mid-quotes decrease when migrating from the primary exchange to the consolidated market. Global IS_{LvM} and CS_{LvM} measures decrease to 38.56% and 43.39%, respectively, implying that informed investors use satellite markets to supply liquidity (Madhavan, 1995) and convey information less through trades, and more through their quoting activities. Informed investors effectively 'cream-skim' the most profitable uninformed trades across multiple trading venues.

3.6.3 Regression Results

This section presents the results of the analysis on fragmentation and its impact on the informativeness of exchange trades versus dark pool trades as well as exchange trades and exchange quotes. The discussion examines the effects of the migration of price forming information in an environment where exchanges offering pre-trade transparency compete with each other for liquidity (intra-market lit fragmentation). Next, the study considers the effect of competition resulting from the migration of liquidity between exchanges offering different levels of pre-trade transparency (inter-market fragmentation). The analysis then focuses on the effect of competition within the dark pool market (intra-market dark fragmentation). Finally, several robustness tests are presented but note that until the robustness test section the study focuses on dark liquidity that exclusively comes from dark pools and avoid all other off-order book transactions.

3.6.3.1 Intra-market Lit Fragmentation

Hypothesis H3-4A states that the informativeness of local exchange trade prices is negatively related to the level of intra-market lit fragmentation. Table 3-7 contains the ordinary least squares (OLS) regression results for local IS_{LvD} and CS_{LvD}, the key measures of price discovery for lit market transaction prices as compared to dark transaction prices. The results align with hypothesis H3-4A that increases in fragmentation among exchanges with pre-trade transparency, that is, increases in intra-market lit fragmentation, lead to a decrease in informativeness of primary market lit trades versus dark trades.

Table 3-7: Regression Results: Lit vs. Dark (Local)

Panel A: Information Share

	IS_{LvD}					
LF	-0.082	-0.053	-0.066	-0.048	-0.039	-0.058
	(-0.92)	(-1.68) *	(-2.19) **	(-2.42) **	(-2.04) **	(-2.11) **
DMS_{DP}	-0.043	-0.035	-0.038	-0.039		-0.183
	(-4.24) ***	(-3.63) ***	(-3.24) ***	(-3.86) ***		(-2.87) ***
DMSA					-0.041	
					(-4.73) ***	
DFDP	-0.006	-0.007	-0.011	-0.010		-0.039
	(-2.04) **	(-2.09) **	(-2.16) **	(-5.47) ***		(-4.31) ***
DFA					-0.013	
					(-4.27) ***	
Ln σ	0.021	0.018	0.032	0.027	0.023	0.057
	(1.38)	(2.01) **	(2.37) **	(2.25) **	(2.14) **	(3.48) ***
Ln BASp	-2.822	-2.346	-3.173	-2.513	-2.623	-1.937
	(-10.41) ***	(-8.74) ***	(-13.25) ***	(-9.11) ***	(-9.57) ***	(2.34) **
Ln MC	0.256	0.324	0.414	0.376	0.392	0.523
	(1.07)	(1.73) *	(2.21) **	(2.03) **	(2.16) **	(1.93) *
Ln Vol	1.836	1.636	1.923	1.785	1.847	3.735
	(14.36) ***	(12.85) ***	(15.68) ***	(13.63) ***	(14.79) ***	(11.23) ***
Fixed Effects	None	Stock	Time	Stock + Time	Stock + Time	Stock + Time
Regression Method	OLS	OLS	OLS	OLS	OLS	2-Stage
Adjusted R2	0.086	0.088	0.091	0.097	0.095	0.104
Number of Obs	312,349	312,349	312,349	312,349	312,349	312,349

Table 3-7: Regression Results: Lit vs. Dark (Local) - continued

Panel B: Component Share

	CS$_{LvD}$					
LF	-0.015	-0.015	-0.008	-0.007	-0.007	-0.002
	(-2.35) **	(-2.34) **	(-3.59) ***	(-3.27) ***	(-4.47) ***	(-5.05) ***
DMS$_{DP}$	-0.064	-0.072	-0.068	-0.065		-0.197
	(-3.74) ***	(-5.12) ***	(-4.24) ***	(-3.80) ***		(-2.90) ***
DMSA					-0.058	
					(-3.23) ***	
DFDP	-0.027	-0.024	-0.027	-0.028		-0.043
	(-5.28) ***	(-4.74) ***	(-5.27) ***	(-5.39) ***		(-5.33) ***
DFA					-0.021	
					(2.17) **	
Ln σ	0.075	0.064	0.057	0.056	0.061	0.056
	(2.43) **	(4.13) ***	(3.27) ***	(3.20) ***	(3.93) ***	(2.15) **
Ln BASp	-1.837	-1.573	-1.674	-1.603	-1.598	-1.638
	(-14.28) ***	(-11.03) ***	(-12.28) ***	(-11.83) ***	(-8.73) ***	(-2.44) **
Ln MC	0.574	0.473	0.347	0.419	0.395	0.032
	(1.04)	(0.94)	(1.74) *	(1.91) *	(1.84) *	(1.85) *
Ln Vol	0.949	0.847	0.684	0.668	0.710	1.259
	(2.33) **	(2.15) **	(3.92) ***	(3.75) ***	(4.01) ***	(5.17) ***
Fixed Effects	None	Stock	Time	Stock + Time	Stock + Time	Stock + Time
Regression Method	OLS	OLS	OLS	OLS	OLS	2-Stage
Adjusted R2	0.078	0.064	0.084	0.083	0.074	0.091
Number of Obs	312,349	312,349	312,349	312,349	312,349	312,349

Note. This table contains the information and component share regressions results for lit transactions prices when compared to dark transaction price: IS$_{LvD}$ and CS$_{LvD}$. IS$_{LvD}$ and CS$_{LvD}$ results are found in Panels A and B, respectively. Both ordinary least squares (OLS) and two-stage least square (2SLS) results are presented. All values are measured with respect to the local primary exchange. LF denotes the fragmentation of lit exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DF denotes the fragmentation of dark exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DF$_{DP}$ consists of trades that originate exclusively from dark pools while DF$_A$ consists of all off-order book transactions. DMS measures the market share of off-order book transactions. DMS$_{DP}$ consists of trades that originate exclusively from dark pools while DMS$_A$ consists of all off-order book transactions. σ is the standard deviation of 1-minute mid-quote returns as measured in basis points. BASp is the average bid-ask spread at the best price level and is weighted by the total depth at that price level. MC is the market capitalisation and is measured by the number of outstanding shares multiplied by the average daily price and is weighted by the total volume transacted at each price. Vol is the total volume consists of the value of shares transacted in the stock over a given stock day and is measured in Euros (€). Vol includes lit and dark transactions, including those originating from dark pool and over-the-counter trades. Volatility, Spread and Market Capitalization are all transformed by the natural logarithm. T-statistics can be found in parentheses with ***, **, and * representing significance at the 1%, 5%, and 10% levels, respectively.

With standard OLS regression coefficients on LF (local fragmentation) ranging from -0.048 to -0.082 (-0.007 to -0.015 for CS_{LvD}) it appears that an increase in the fragmentation of the lit market coincides with a decrease in the price discovery of transactions that result from the use of displayed liquidity on the local primary market. Note that only 3 of the 4 measures for IS_{LvD} are found to be significant. One might conclude that lit market fragmentation causes informed trading to leave the local exchange and migrate to dark pools.

In contrast, hypothesis H3-4B expects the opposite for the global market and states the informativeness of consolidated global exchange trade prices is positively related to the level of intra-market lit fragmentation. The results in Table 3-8 show that the lit fragmentation (LF) coefficient in the global context, that is, when considering information across all exchanges rather than simply the primary exchange, shows decrease in price discovery of lit market trades in the consolidated market compared to the primary market.

Table 3-8: Regression Results: Lit vs. Dark (Global)

Panel A: Information Share

	IS_{LvD}					
LF	-0.011	-0.003	-0.012	-0.009	-0.009	-0.005
	(-2.36) **	(0.67)	(-2.41) **	(-2.15) **	(-2.12) **	(-3.19) ***
DMS_{DP}	-0.014	-0.018	-0.024	-0.019		-0.092
	(-2.37) **	(-1.99) **	(-4.29) ***	(-6.25) ***		(-2.33) **
DMSA					-0.023	
					(-3.52) ***	
DFDP	-0.002	-0.006	-0.008	0.008		-0.014
	(-2.48) **	(-1.42)	(-2.38) **	(-2.10) **		(-2.98) ***
DFA					-0.002	
					(-5.25) ***	
Ln σ	-0.007	0.008	0.057	0.013	0.004	0.022
	(-1.06)	(2.14) **	(5.24) ***	(3.53) ***	(2.30) **	(6.20) ***
Ln BASp	-0.902	-1.090	-0.891	-0.917	-1.432	-2.58
	(3.15) ***	(-2.49) **	(-4.30) ***	(-2.91) ***	(-4.29) ***	(-2.11) **
Ln MC	0.492	0.529	0.819	0.704	0.828	0.392
	(1.69) *	(1.91) *	(2.47) **	(0.85)	(2.16)	(1.71) *
Ln Vol	2.947	2.048	1.589	3.014	1.495	2.489
	(3.53) ***	(2.85) ***	(2.53) **	(4.21) ***	(4.25) ***	(2.08) **
Fixed Effects	None	Stock	Time	Stock + Time	Stock + Time	Stock + Time
Regression Method	OLS	OLS	OLS	OLS	OLS	2-Stage
Adjusted R2	0.056	0.051	0.057	0.061	0.057	0.063
Number of Obs	312,349	312,349	312,349	312,349	312,349	312,349

Table 3-8: Regression Results: Lit vs. Dark (Global) - continued

Panel B: Component Share

	CSLvD					
LF	-0.008	-0.012	-0.005	-0.007	-0.003	-0.015
	(-2.42) **	(-1.87) *	(-2.10) **	(-2.39) **	(-4.94) ***	(-3.89) ***
DMS_{DP}	-0.043	-0.033	-0.042	-0.058		-0.098
	(-2.59) ***	(-2.17) **	(-3.53) ***	(-3.01) ***		(-2.38) **
DMSA					-0.069	
					(-3.23) ***	
DFDP	0.014	-0.039	-0.021	-0.015		-0.021
	(-2.67) ***	(-2.52) **	(-2.98) ***	(-2.73) ***		(-3.49) ***
DFA					-0.021	
					(-1.99) **	
Ln σ	0.059	0.070	0.049	0.039	0.050	0.083
	(5.63) ***	(3.89) ***	(2.51) **	(5.28) ***	(8.29) ***	(2.84) ***
Ln BASp	-0.305	-0.520	-0.202	-0.586	-0.617	-0.948
	(-6.29) ***	(-3.28) ***	(-4.30) ***	(-5.23) ***	(-3.50) ***	(-6.77) ***
Ln MC	0.294	0.328	0.211	0.593	0.847	0.105
	(1.81) *	(1.44)	(2.07) **	(2.47) **	(1.94) *	(2.19) **
Ln Vol	1.493	0.927	0.802	1.573	0.721	2.149
	(2.41) **	(1.39)	(2.78) ***	(3.20) ***	(2.71) ***	(2.89) ***
Fixed Effects	None	Stock	Time	Stock + Time	Stock + Time	Stock + Time
Regression Method	OLS	OLS	OLS	OLS	OLS	2-Stage
Adjusted R2	0.104	0.072	0.124	0.114	0.058	0.079
Number of Obs	312,349	312,349	312,349	312,349	312,349	312,349

Note. This table contains the information and component share regressions results for lit transactions prices when compared to dark transaction price: IS_{LvD} and CS_{LvD}. IS_{LvD} and CS_{LvD} results are found in Panels A and B, respectively. Both ordinary least squares (OLS) and two-stage least square (2SLS) results are presented. All values are measured with respect to the consolidated global order book. LF denotes the fragmentation of lit exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DF denotes the fragmentation of dark exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DF_{DP} consists of trades that originate exclusively from dark pools while DF_A consists of all off-order book transactions. DMS measures the market share of off-order book transactions. DMS_{DP} consists of trades that originate exclusively from dark pools while DMS_A consists of all off-order book transactions. σ is the standard deviation of 1-minute mid-quote returns as measured in basis points. BASp is the average bid-ask spread at the best price level and is weighted by the total depth at that price level. MC is the market capitalisation and is measured by the number of outstanding shares multiplied by the average daily price and is weighted by the total volume transacted at each price. Vol is the total volume consists of the value of shares transacted in the stock over a given stock day and is measured in Euros (€). Vol includes lit and dark transactions, including those originating from dark pool and over-the-counter trades. Volatility, Spread and Market Capitalization are all transformed by the natural logarithm. T-statistics can be found in parentheses with ***, **, and * representing significance at the 1%, 5%, and 10% levels, respectively.

With an IS_{LvD} LF coefficients ranging from -0.003 to -0.012 for IS_{LvD} (-0.005 to -0.012 for CS_{LvD}) the results suggest that, while some informed activity does migrate to the dark, more informed activity is leaving the primary markets compared to the consolidated market. While the negative coefficient does not support hypothesis H3-4B, it does imply that participants in the consolidated market have less of a need to leave the lit exchange when lit markets fragment. By doing so informed investors are also able avoid non-execution risks associated with dark pools whilst continuing to make it difficult for other investors to infer their intentions due to the distributed nature of their trades. However, the result is still a net loss in information resulting from lit trade prices.

Next, the effects of intra-market lit fragmentation on the informativeness of exchange prices compared to quotes is analysed. Increased fragmentation is associated with increased trading volume as multiple markets can only be sustained if there is sufficient liquidity to support it (Mendelson, 1987). The formation of new markets can attract a greater proportion of liquidity traders who then decrease the informativeness of prices (Chowdhry & Nanda, 1991). Informed investors favour supplying liquidity in highly fragmented markets in order to pick-off only the most profitable trades (Bessembinder & Kaufman, 1997; Easley et al., 1996). As a result, the study expects intra-market lit fragmentation to decrease the amount in which exchange prices reveal price forming information as compared to quotes.

Specifically, hypothesis H3-2B states that the informational content of lit exchange mid-quotes is positively related to market fragmentation. This is represented in the results by a negative coefficient for the informativeness of trade prices compared to mid-quotes. The results in Table 3-9 supports the hypothesis where the coefficients for local IS_{LvM} and CS_{LvM} range from -0.018 to -0.022 and -0.025 to -0.028 respectively. This also provides support for hypothesis H3-4A. This indicates that the informativeness of exchanges trades as compared to quotes does deteriorate with greater intra-market lit fragmentation. The results are robust across the global consolidated market in Table 3-10 with global IS_{LvM} and CS_{LvM} coefficients ranging from -0.144 to -0.227 and -0.026 to -0.036, respectively. This result is contradictory to the hypothesis H3-4B. The increased informativeness of quotes, that is, the decreased informativeness of trade prices compared to mid-quotes, is associated with higher levels of adverse selection in the lit market and is consistent with the notion that the most profitable uninformed trades ‘skimmed’ by informed liquidity providers (Bessembinder & Kaufman, 1997; Easley et al., 1996). Table 3-9 and Table 3-10 shows that as volatility and quoted spreads increase, that is, as adverse selection increases, both local and global prices contribute less towards price discovery than quotes. This is further supported through the positive correlation coefficient (Table 3-2) between volatility and intra-market lit fragmentation (LF). The inverse relationship between LF and quoted spreads, as indicated by a negative correlation coefficient of 0.3965, implies that increased fragmentation in the lit market is associated with an increase in uninformed trading.

This, however, contradicts the previous statement and supports the notion that greater intra-market lit fragmentation reduces the amount of informed trading in the market and as a result, should reduce adverse selection risk. Though the correlation between these two measures is weak, it does not noticeably discredit the previous statement regarding the increase in adverse selection.

Table 3-9: Regression Results: Price vs. Mid-Quote (Local)

Panel A: Information Share

	IS_{LvM}					
LF	-0.021	-0.019	-0.022	-0.018	-0.020	-0.043
	(-4.47) ***	(-4.36) ***	(-5.22) ***	(-4.19) ***	(-3.88) ***	(-4.95) **
DMS_{DP}	-0.026	-0.026	-0.025	-0.024		-0.052
	(-6.07) ***	(-5.89) ***	(-5.27) ***	(-4.99) ***		(-4.27) ***
DMSA					-0.025	
					(-5.37) ***	
DFDP	-0.018	-0.012	-0.013	-0.006		-0.035
	(-0.24)	(-2.90) ***	(-2.92) ***	(-2.75) ***		(-4.29) ***
DFA					-0.011	
					(-3.20) ***	
Ln σ	-0.102	-0.096	-0.085	-0.083	-0.088	-0.124
	(-2.36) **	(-2.28) **	(-2.19) **	(-2.78) ***	(-2.98) ***	(-3.86) ***
Ln BASp	-1.246	-0.837	-1.314	-1.294	-1.285	-0.095
	(-1.78) *	(-1.37)	(-2.35) **	(-2.38) **	(-2.29) **	(-2.31) **
Ln MC	0.152	0.162	0.135	0.134	0.145	0.725
	(1.78) *	(1.83) *	(1.69) *	(2.18) **	(1.72) *	(0.96)
Ln Vol	-0.427	-0.356	-0.523	-0.493	-0.458	-0.395
	(-2.46) **	(-2.40) **	(-3.02) ***	(-2.86) ***	(-2.75) ***	(-2.37) **
Fixed Effects	None	Stock	Time	Stock + Time	Stock + Time	Stock + Time
Regression Method	OLS	OLS	OLS	OLS	OLS	2-Stage
Adjusted R2	0.063	0.057	0.073	0.079	0.068	0.083
Number of Obs	312,349	312,349	312,349	312,349	312,349	312,349

Table 3-9: Regression Results: Price vs. Mid-Quote (Local) - continued

Panel B: Component Share

	CSLvM					
LF	-0.028	-0.026	-0.025	-0.025	-0.021	-0.194
	(-4.23) ***	(-2.96) ***	(-3.84) ***	(-3.83) ***	(-3.26) ***	(-2.97) **
DMS_{DP}	-0.050	-0.038	-0.048	-0.051		-0.937
	(-7.23) ***	(-6.37) ***	(-7.05) ***	(-7.34) ***		(-6.27) ***
DMSA					-0.049	
					(-5.28) ***	
DFDP	-0.038	-0.032	-0.028	-0.025		-0.083
	(-0.65)	(-0.39)	(-2.25) **	(-2.18) **		(-3.94) ***
DFA					-0.027	
					(-4.28) ***	
Ln σ	-0.102	-0.085	0.121	0.092	0.084	0.139
	(3.39) ***	(-2.82) ***	(3.67) ***	(3.13) ***	(2.78) ***	(4.28) ***
Ln BASp	-3.275	2.452	-4.285	-3.482	2.903	4.284
	(-1.26)	(0.94)	(-1.48)	(-1.38)	(1.10)	(2.41) **
Ln MC	-0.285	-0.278	-0.319	-0.428	-0.285	-0.38234
	(-1.73) *	(-1.70) *	(-1.84) *	(-1.91) *	(-1.72) *	(-1.71) **
Ln Vol	-0.104	-0.085	-0.132	-0.126	-0.136	-0.087
	(-2.25) **	(-2.05) **	(-2.69) ***	(-2.61) ***	(-2.81) ***	(2.09) **
Fixed Effects	None	Stock	Time	Stock + Time	Stock + Time	Stock + Time
Regression Method	OLS	OLS	OLS	OLS	OLS	2-Stage
Adjusted R2	0.047	0.048	0.053	0.063	0.048	0.068
Number of Obs	312,349	312,349	312,349	312,349	312,349	312,349

Note. This table contains the information and component share regressions results for market mid-quotes compared to lit market trades: IS_{LvM} and CS_{LvM}. IS_{LvM} and CS_{LvM} results are found in Panels A and B, respectively. Both ordinary least squares (OLS) and two-stage least square (2SLS) results are presented. All values are measured with respect to the primary order book. LF denotes the fragmentation of lit exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DF denotes the fragmentation of dark exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DF_{DP} consists of trades that originate exclusively from dark pools while DF_A consists of all off-order book transactions. DMS measures the market share of off-order book transactions. DMS_{DP} consists of trades that originate exclusively from dark pools while DMS_A consists of all off-order book transactions. σ is the standard deviation of 1-minute mid-quote returns as measured in basis points. BASp is the average bid-ask spread at the best price level and is weighted by the total depth at that price level. MC is the market capitalisation and is measured by the number of outstanding shares multiplied by the average daily price and is weighted by the total volume transacted at each price. Vol is the total volume consists of the value of shares transacted in the stock over a given stock day and is measured in Euros (€). Vol includes lit and dark transactions, including those originating from dark pool and over-the-counter trades. Volatility, Spread and Market Capitalization are all transformed by the natural logarithm. T-statistics can be found in parentheses with ***, **, and * representing significance at the 1%, 5%, and 10% levels, respectively.

As exchanges offering pre-trade transparency fragment and we observe increased intra-market lit-fragmentation, lit market prices begin to contain more private information than their dark market counterparts. The results are consistent with prior research that finds an increase in the number of trading venues with pre-trade transparency allows informed investors to conceal their intentions more easily (Madhavan, 1995).

Table 3-10: Regression Results: Price vs. Mid-Quote (Global)

Panel A: Information Share

	IS_{LvM}					
LF	-0.227	-0.194	-0.154	-0.144	-0.152	-0.393
	(-11.28) ***	(-9.94) ***	(-8.73) ***	(-8.17) ***	(-9.47) ***	(-9.57) ***
DMS_{DP}	-0.057	-0.046	-0.053	-0.049		-0.072
	(-9.28) ***	(-8.37) ***	(-8.93) ***	(-8.56) ***		(-10.24) ***
DMSA					-0.037	
					(-8.74) ***	
DFDP	-0.015	-0.015	-0.009	-0.008		-0.017
	(-0.94)	(-1.12)	(-3.63) ***	(-3.53) ***		(-3.25) ***
DFA					-0.013	
					(-4.24) ***	
Ln σ	-0.827	-1.239	-0.647	-0.749	-0.569	-0.619
	(-2.22) **	(-2.32) **	(-2.05) **	(-2.85) ***	(-3.02) ***	(-2.96) ***
Ln BASp	-0.936	-0.873	-0.463	-0.363	-0.473	-0.519
	(-1.83) *	(-1.76) *	(-2.43) **	(-2.12) **	(-2.49) **	(-4.18) **
Ln MC	2.493	1.624	0.235	0.227	0.343	0.402
	(0.84)	(0.39)	(3.27) ***	(3.06) ***	(4.28) ***	(5.28) ***
Ln Vol	-0.352	-0.522	-0.278	-0.325	-0.274	-0.230
	(-3.04) ***	(-2.47) **	(-2.67) ***	(-2.84) ***	(-2.61) ***	(-2.35) **
Fixed Effects	None	Stock	Time	Stock + Time	Stock + Time	Stock + Time
Regression Method	OLS	OLS	OLS	OLS	OLS	2-Stage
Adjusted R2	0.056	0.051	0.057	0.061	0.057	0.063
Number of Obs	312,349	312,349	312,349	312,349	312,349	312,349

Table 3-10: Regression Results: Price vs. Mid-Quote (Global) - continued

Panel B: Component Share

	CSLvM					
LF	-0.036	-0.031	-0.027	-0.026	-0.027	-0.057
	(-3.28) ***	(-2.94) ***	(-2.79) ***	(-2.66) ***	(-2.84) ***	(-4.79) ***
DMS_{DP}	-0.027	-0.025	-0.018	-0.016	-0.011	-0.038
	(-13.29) ***	(-12.25) ***	(-10.38) ***	(-9.85) ***	(-9.93) ***	(-15.37) ***
DMSA						
DFDP	-0.016	-0.014	-0.008	-0.007		-0.026
	(-4.02) ***	(-3.84) ***	(-2.95) ***	(-3.28) ***		(-6.24) ***
DFA					-0.002	
					(-3.02) ***	
Ln σ	-0.522	-0.518	-0.483	-0.462	-0.643	-0.552
	(-3.47) ***	(-3.38) ***	(-3.18) ***	(-2.94) ***	(-5.29) ***	(-4.28) ***
Ln BASp	-0.937	-1.232	0.047	-0.523	-0.175	0.061
	(-1.03)	(-1.49)	(0.10)	(-1.75) *	(-0.37)	(1.84) *
Ln MC	0.453	1.284	0.839	0.948	1.127	0.583
	(0.36)	(0.94)	(0.68)	(0.79)	(0.90)	(1.71) *
Ln Vol	0.026	0.026	0.020	0.019	0.008	0.025
	(3.75) ***	(3.68) ***	(3.18) ***	(3.06) ***	(2.95) ***	(2.38) **
Fixed Effects	None	Stock	Time	Stock + Time	Stock + Time	Stock + Time
Regression Method	OLS	OLS	OLS	OLS	OLS	2-Stage
Adjusted R2	0.037	0.046	0.049	0.053	0.047	0.054
Number of Obs	312,349	312,349	312,349	312,349	312,349	312,349

Note. This table contains the information and component share regressions results for market mid-quotes compared to lit market trades: IS_{LvM} and CS_{LvM}. IS_{LvM} and CS_{LvM} results are found in Panels A and B, respectively. Both ordinary least squares (OLS) and two-stage least square (2SLS) results are presented. All values are measured with respect to the consolidated global order book. LF denotes the fragmentation of lit exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DF denotes the fragmentation of dark exchanges and is represented by 1- Herfindahl-Hirschman Index (HHI). DF_{DP} consists of trades that originate exclusively from dark pools while DF_A consists of all off-order book transactions. DMS measures the market share of off-order book transactions. DMS_{DP} consists of trades that originate exclusively from dark pools while DMS_A consists of all off-order book transactions. σ is the standard deviation of 1-minute mid-quote returns as measured in basis points. BASp is the average bid-ask spread at the best price level and is weighted by the total depth at that price level. MC is the market capitalisation and is measured by the number of outstanding shares multiplied by the average daily price and is weighted by the total volume transacted at each price. Vol is the total volume consists of the value of shares transacted in the stock over a given stock day and is measured in Euros (€). Vol includes lit and dark transactions, including those originating from dark pool and over-the-counter trades. Volatility, Spread and Market Capitalization are all transformed by the natural logarithm. T-statistics can be found in parentheses with ***, **, and * representing significance at the 1%, 5%, and 10% levels, respectively.

Those with valuable private information need not resort to placing orders in dark pools where greater non-execution probability resulting from informed investors clustering on the heavy side of the market exposes them to potential increases in transaction costs (Zhu, 2014) as do delayed executions during which adverse price changes may occur. Also, investors who are able to access multiple venues simultaneously through the use of smart order routing technology (SORT) can offset the 'thinness' of the exchanges with price diversification benefits and experience reduced weighted average price variance (Mendelson, 1987). Therefore, we expect to see an increase in the level in which global exchange prices contribute to price discovery compared to trade prices originating in dark pools. However, local exchange prices, or those originating from a stock's primary exchange, experience a deterioration in their contributions to price discovery as compared to the more inherently fragmented dark pool market. These findings suggest that as the absorptive capacity of the primary exchange decreases due to increased competition from other exchanges providing pre-trade transparency, investors are forced to look towards alternative markets in order to avoid adverse price changes (Pagano, 1989) with dark pools being among the set alternatives.

3.6.3.2 Inter-market Fragmentation

Both limit and market orders are observed to contain price forming information (Kaniel & Liu, 2006). Therefore, any amount of dark pool activity is expected to have an adverse effect on the extent to which lit exchange prices contribute price adjusting information when compared to dark orders, resulting in a negative regression coefficient. Hypothesis H3-5A states that there is a negative relationship between inter-market fragmentation, that is, the migration of liquidity from lit exchanges to dark exchanges, and the informativeness of lit exchange trade prices compared to dark exchange trade prices. This hypothesis implies that if dark pools attract information that is as informative as the information found in lit exchanges then it is expected that the regression coefficient for the market share of dark pools (DMS_{DP}) to be -1. This suggests that a 1% increase in the market share of dark pools results in a 1% decrease in the informativeness of lit trades. A coefficient below (above) -1 would indicate that trades migrating to dark pools contain proportionally less (more) information than noise. Consistent with the findings of Zhu (2014) and L. Ye (2016), and given the previous results in Tables 3-7 and 3-8 conveying the informativeness of lit versus dark prices, dark pools are expected to attract less informed investors on average.

Revisiting Table 3-7, the coefficients for DMS_{DP} pertaining to IS_{LvD} and CS_{LvD} to range from -0.035 to -0.043 and -0.064 to -0.072, respectively supporting H3-5A. These results reinforce the notion that dark pool transactions are substantially less informed than those on the primary quoting exchange. This again supports the predictions of Zhu (2014) in that dark pools attract predominately uninformed trades as informed investors would be subject to greater instances of non-execution due to their tendency to cluster on the same side of the order book. An alternate explanation is that the findings support the results found by L. Ye (2016) whereby investors with highly precise information trade in the quoting exchange while those with information of moderate precision opt to trade in the dark pool as they can help mitigate informational risk. The findings of L. Ye (2016) support those of Zhu (2014) in that dark pools attract investors that are less than perfectly informed and, as they gain market share, improve the overall quality of information in the quoting exchange.[30] It must be noted, however, that one drawback to measuring the informativeness of dark pools is that information is conveyed to the market only after a successful transaction. This means that any intentions to trade amongst investors, and the subsequent information these signals contain, are removed from market consideration until after the fact. Failed transactions, on the other hand, are never considered and their information is concealed from the market entirely.

Hypothesis H3-5C states that the informativeness of local trade prices is more sensitive to changes in inter-market fragmentation compared to global trade prices. Table 3-7 and Table 3-8 convey a similar, albeit reduced, the impact of inter-market fragmentation. IS_{LvD} and CS_{LvD} measures in Table 3-8 display coefficients ranging from -0.014 to -0.024 and -0.033 to -0.058, respectively, which is less negative than the local trade market. Global markets tend to be more informative than local ones as they consist of both the primary exchange and several competing exchanges. Consequently, they encapsulate a greater proportion of the available information and are less impacted by the migration of trading activity to the dark market compared to the local exchange.

Hypothesis H3-5B states that inter-market fragmentation results in a greater concentration of informed investors, compared uninformed investors, in lit exchanges. The higher levels of

[30] Unlike Zhu (2012), L. Ye's (2016) findings are dependent on the level of noisy information in the market. While Zhu's (2012) model predicts that dark pools strictly improve price discovery in the quoting exchange, Ye's (2016) results only come to the same conclusion when noise is at a minimum, that is, when information precision is high. When information precision is low informed investors opt to trade in the dark pool.

informed trading are associated with greater adverse selection risk with one indicator of this being wider bid-ask spreads (Glosten & Milgrom, 1985). This is evident in the results through the (mostly) positive coefficients between quoted spreads and both IS_{LvM} and IS_{LvM} (Table 3-9 and 3-10). Therefore, while increases to the market share of dark pools improve the quality of information on the quoting exchanges, it comes at the cost of increased adverse selection risk in the quoting exchanges as uninformed investors favour trading in the dark pool. Table 3-2 contains further evidence of increased adverse selection risk with dark pool market share (DMS_{DP}) displaying a positive correlation to both quoted spreads (0.1055) and volatility (0.1096).

On the topic of volatility, L. Ye (2016) predicts that when volatility is high, the informational advantage, that is, the benefit of acquiring private information, is high and adding a dark pool enhances price discovery. However, if volatility is low and below a critical threshold, then adding a dark pool impairs price discovery. This largely depends on the noise in the market as expressed by the ratio of informed to uninformed investors. When risk is high, informed traders face higher potential profits and therefore, would rather stay in the quoting exchange when compared to uninformed liquidity traders. As a result, adding a dark pool increases the signal to noise ratio and improves the informativeness of the lit exchange trades.

Table 3-7 reports a positive coefficient between volatility and the price discovery of lit exchange trades ranging from 0.018-0.032. Consistent with the findings of L. Ye (2016), as risk increases the informativeness of the primary exchange prices also increase due to the informational advantage experienced by the informed traders.

The advantages informed traders experience due to their access to superior information affords them the opportunity to safely supply liquidity when adverse selection risks are high (Rindi, 2008). We have shown that increased use of dark liquidity is associated with greater adverse selection in quoting exchanges due to the propensity for dark pools to attract primarily uninformed investors. Therefore, exchange quotes are expected to take on a greater role in conveying price adjusting information compared to exchange trade prices.

The results support hypothesis H3-2B that trade migration from quoting exchanges to dark pools is associated with an increase in the informativeness of exchange quotes compared to exchange prices. Table 3-9 and Table 3-10 show negative coefficients across all regressions for DMS_{DP} on IS_{LvM} and CS_{LvM}. The negative coefficients for both quoted spreads and volatility also contribute to the conclusion that increases to adverse selection are associated with exchange quotes taking on a greater role in compounding information as informed investors face a comparative advantage in supplying liquidity. Comerton-Forde and Putniņš (2015) also remark that dark trading makes it easier for brokers to internalise trades and they prefer to do so with uninformed liquidity due to the lower adverse selection costs. This provides further support for the increase in adverse selection across quoting exchanges as the actions of the brokers help to concentrate informed activity in said markets.

3.6.3.3 Intra-Market Dark Fragmentation

To the best of our knowledge, to date there are no studies have investigated the impact of intra-market dark fragmentation on price discovery. Studies such as those by M. Ye (2012), Zhu (2014) and L. Ye (2016) focus on the introduction of a single dark pool to the existing market. However, a previous empirical study by Majtyka et al. (2015) has shown a strong relationship between the market share of dark pools and the level of fragmentation among dark pools. Therefore, as with quoting exchanges, the predictions are based on the assumption that the market for dark liquidity can only sustain greater levels of fragmentation if there exists sufficient liquidity to support multiple exchange pools.

When dark markets were in their infancy and supported few customers, it is likely that it was difficult to find an opposing party to the trade. However, since the introduction of MiFID dark markets have increased in popularity and now consist of 9.74% of total trading volume within the sample versus 4.38% during the earlier periods. This supports the idea that a fragmented dark order book today can support customers to the same extent as a consolidated dark order book during the introduction of MiFID and that the number of dark pools can fluctuate in order to serve a growing client base.

Under such circumstances, an increase in dark pool fragmentation is expected to have a similar effect on price discovery as increases to the market share of dark pools. Informed investors continue to favour lit exchanges as fragmentation in the dark market distributes liquidity across competing dark liquidity providers and increases non-execution risk for informed investors in any given dark pool. Therefore, new dark pools must attract uninformed liquidity in order to sustain activity within the pool. This, in turn, concentrates informed investors on quoting exchanges which leads to increased adverse selection risk in the said exchanges. Greater adverse selection risk incentivises informed investors into supplying liquidity in order to profit from their informational advantage.

Support for the hypotheses H3-6A to C surrounding intra-market dark fragmentation can be found in Tables 3-7 to 3-10. As with the market share of dark pools, dark market fragmentation (DF_{DP}) is associated with a concentration of informed order flow in quoting exchanges with the coefficients for DF across IS_{LvD} and CS_{LvD} measures being much closer to 0 than they are to -1. This result supports hypothesis H3-6A that there is a negative relationship between intra-market dark fragmentation and the informativeness of lit exchange trade prices compared to dark exchange trade prices.

The IS_{LvM} and CS_{LvM} coefficients also continue to be negative which supports the hypothesis H3-6B that intra-market dark fragmentation results in a greater concentration of informed investors, compared uninformed investors, in lit exchanges. That is, informed investors favour supplying liquidity when exposed to greater adverse selection risk associated with trading in quoting exchanges. However, these relationships are not as strong for DF_{DP} as they are with DMS_{DP}. DF_{DP} coefficients are only significant for 5 of the 8 regressions performed on IS_{LvD} and CS_{LvD} measures in Table 3-10. IS_{LvM} and CS_{LvM} measures are slightly more favourable with 6 of the 8 regression coefficients being significant. This supports hypothesis H3-6C that the informativeness of local trade prices is more sensitive to changes in inter-market fragmentation compared to global trade prices.

3.6.3.4 Robustness Checks

Variations to both the methods and data are explored to test the robustness of the results. First, a two-stage least squares (2SLS) regression is run to account for the effects of endogeneity within the three key fragmentation measures and instrumental variables: lit fragmentation (LF), dark pool market share (DMS), and dark fragmentation (DF). Note that the analysis focuses on DMS and DF figures that consist exclusively of dark pool activity. In the first stage the model for daily lit order book fragmentation for stock i at time t ($LF_{i,t}$)is as follows:

$$LF_{i,t} = b_0 + b_1 AVGLF_t + b_2 NumVL_{i,t} + b_3 lnVol_{i,t} + b_4 \sigma_{i,t} + b_5 lnBASp_{i,t} + b_6 lnMC_{i,t} + \mu_{i,t} \qquad (22)$$

where $AVGLF_t$ is the average measure of lit fragmentation across all sampled firms at time t and $NumVL_{i,t}$ is the number of distinct visible trading venues selling stock i at time t, with the remainder being the control variables identified in the original panel regression inequation 17. The first stage model for dark pool market share for stock *i* at time *t* ($DMS_{i,t}$) is as follows:

$$DMS_{i,t} = b_0 + b_1 AVGDMS_t + b_2 NumVD_t + b_3 lnVol_{i,t} + b_4 \sigma_{i,t} + b_5 lnBASp_{i,t} + b_6 lnMC_{i,t} + \mu_{i,t} \quad (23)$$

where $AVGDMS_t$ is the average dark pool market share across all sampled firms at time *t* and $NumVD_{i,t}$ is the number of distinct dark trading venues offering stock i at time t, with the remainder being the standard control variables. Finally, the first stage model for dark fragmentation for stock *i* at time t ($DF_{i,t}$) is as follows:

$$DF_{i,t} = b_0 + b_1 AVGDF_t + b_2 NumVD_t + b_3 lnVol_{i,t} + b_4 \sigma_{i,t} + b_5 lnBASp_{i,t} + b_6 lnMC_{i,t} + \mu_{i,t} \quad (24)$$

where $AVGDF_t$ is the average measure of dark pool fragmentation across all sampled firms at time t, $NumVD_{i,t}$ is the number of distinct dark trading venues offering stock *i* at time *t*, and the standard control variables.

In the second stage our key measures of price discovery (IS_{LvD}, CS_{LvD}, IS_{LvM}, and CS_{LvM}) are regressed using the standard panel regression model, Equation 17, however this time the values of each key regressor are replaced with the those from the first stage regression. Note that this is conducted for both local and global measures of price discovery.

The final column for each price discovery measure in Tables 3-7 to 3-10 displays the results of our 2SLS regression. The results are consistent with the previous findings and support the conclusions that fragmentation of any kind increases adverse selection risk in the standard quoting (lit) exchanges by encouraging a disproportional number of informed investors to trade on lit exchanges as opposed to dark pools. This, in turn, increases the informativeness of order book quotes as informed investors face a comparative advantage in supply liquidity during such periods to the superior nature of their information.

Second, the standard panel regression is adjusted to incorporate all off-order book activity, including standard over-the-counter transactions, into the dark measures to account for other transactions that originate without pre-trade transparency. The results are reported in Tables 3-7 to 3-10 where DMS_A and DF_A values are used in place of DMS_{DP} and DF_{DP}, respectively. The signs of the regression coefficients imply a similar effect as with the previous result. This implies that over-the-counter transactions consist of a similar mix of informed and uninformed trading as dark pools and that dark pools may simply be used as a more automated form of off-order book transaction. As a result, dark pools may not have any more of a negative impact on market conditions and price discovery than other liquidity that operates without pre-trade transparency.

Lastly, all three sample periods are tested individually. This additional analysis does not produce any key differences in the results, though that *DF* coefficients lose some significance during the earliest sample window. The implication is that dark pools experienced a slight change in the mix of clientele as the competition among dark pools, and the resulting fragmentation it caused, was more in its infancy and accounted for less volume when compared to later stages.

3.7 Summary of Results

The results of the hypothesis testing are summarised in Table 3-11. The study tested six main hypotheses, some with multiple subparts. The analysis and results support most of the hypothesised relations. However, due to the assumption tests in Section 3.5.4.4, the final coefficients may be affected by the presence of multicollinearity in the independent variables.

Table 3-11: Summary of Hypothesis Testing and Results

Hypothesis	Result Table	Conclusion
H3-1: Lit exchange trade prices contain more information than dark pool trade prices.	3-6	Accept
H3-2A: Lit exchange mid-quotes contain more information than lit exchange trade prices.	3-6	Accept
H3-2B: The informational content of lit exchange mid-quotes is positively related to market fragmentation.	3-9 3-10	Accept
H3-3A: Lit exchange trade prices in the consolidated global market contain more information than lit exchange trade prices in local primary exchange.	3-6	Accept
H3-3B: Lit exchange mid-quotes in the consolidated global market contain more information than lit exchange mid-quotes in local primary exchange.	3-6	Accept
H3-4A: The informativeness of local exchange trade prices is negatively related to the level of intra-market lit fragmentation.	3-7	Accept
H3-4B: The informativeness of consolidated global exchange trade prices is positively related to the level of intra-market lit fragmentation.	3-8	Reject
H3-5A: There is a negative relationship between inter-market fragmentation and the informativeness of lit exchange trade prices compared to dark exchange trade prices.	3-7 3-8	Accept
H3-5B: Inter-market fragmentation results in a greater concentration of informed investors, compared uninformed investors, in lit exchanges.	3-9 3-10	Accept
H3-5C: The informativeness of local trade prices is more sensitive to changes in inter-market fragmentation compared to global trade prices.	3-7 3-8	Accept
H3-6A: There is a negative relationship between intra-market dark fragmentation and the informativeness of lit exchange trade prices compared to dark exchange trade prices.	3-7 3-8	Accept
H3-6B: Intra-market dark fragmentation results in a	3-9	Accept

	greater concentration of informed investors, compared uninformed investors, in lit exchanges.	3-10	
H3-6C:	The informativeness of local trade prices is more sensitive to changes in inter-market fragmentation compared to global trade prices.	3-7 3-8	Accept

3.8 Conclusion

The findings in this chapter answer RQ2. The result support theory presented by Zhu (2014) in that lit prices contain substantially more information than dark prices. Mid-quotes on lit exchanges are more informative than lit prices. Regarding fragmentation, the results align with the hypothesis and indicate that increases in fragmentation among quoting (lit) exchanges lead to a decrease in the informativeness of primary market lit trades versus dark trades. When considering information across all exchanges, rather than simply the primary exchange, the results suggest an increase in price discovery of lit market trades**. I**nformative trades appear to leave the dark market and instead choose to spread their activity across several lit exchanges, taking advantage of smart order routing technology (SORT), in order to continue concealing their intentions. Doing so helps informed investors avoid non-execution risks (Zhu, 2014) associated with dark pools by offsetting the 'thinness' of fragmented markets (Mendelson, 1987) while continuing to disguise their intentions from the market (Madhavan, 1995).

The informativeness of exchanges trades as compared to quotes does, in fact, deteriorate with greater intra-market lit fragmentation suggesting that intra-market lit fragmentation is associated with higher levels of adverse selection in the lit market. This is further supported by the negative relationship between price discovery and volatility and is consistent with the notion that the most profitable uninformed trades are being 'skimmed' by informed liquidity providers (Bessembinder & Kaufman, 1997; Easley et al., 1996).

Dark market share coefficients, which measure the inter-market fragmentation between lit and dark exchanges, provide additional support that dark transactions are substantially less informed that lit transactions. They are consistent with the theoretical implications Zhu (2014) and L. Ye (2016). Informed investors are discouraged from relying on dark pools as they tend to experience greater non-execution risk since they cluster on the heavy side of the market. Once again, fragmentation is associated with greater adverse selection risk in quoting exchanges as informed investors use their informational advantage to supply liquidity (Rindi, 2008). The effects are greater in local exchanges as global market benefit from a more diverse subset of investors.

The study reported in this chapter is the first study to investigate the impact of intra-market dark fragmentation on price discovery. The findings show that a fragmented dark order book today can support customers to the same extent as a consolidated dark order book during the introduction of MiFID and that the number of dark pools can fluctuate in order to serve a growing client base. This results in dark market fragmentation being associated with a concentration of informed order flow in quoting exchanges. As expected, these results are consistent with those of inter-market fragmentation and the growing popularity of dark pools. As dark pools fragment, the market continues to experience greater adverse selection risk associated with the concentration of informed trading on quoting exchanges though these results are less significant than those for inter-market fragmentation.

Overall the empirical results support the taxonomical framework established in Chapter 2, Figure 2-12. Transaction costs are the main driver of equity markets fragmentation into lit and dark segments. In addition, the results show that dark markets help complete lit markets and are an important motivator of this sort of market modification.

Chapter 4: Fragmentation & Price Discovery in Cryptocurrency Markets

4.1 Introduction

Cryptocurrencies, such as Bitcoin, demonstrate that individuals can exchange financial assets amongst each other without the need for a financial middleman to facilitate the transaction. This is in large part due to a key technological innovation, the distributed ledger, which allows for the non-centralised settling and clearing of transactions. By maintaining the record of ownership across many devices, the technology behind cryptocurrencies negates the need for a central trusted entity. Distributed ledgers also make it easier to set up new cryptocurrency exchanges. Cryptocurrency markets are an example of technology motivated new product innovations in fragmented markets (see Figure 2-12).

In equity markets, new exchanges attract informed trades from the dominant exchange making collecting all necessary price adjusting information more difficult. The result is a deterioration in the price discovery process. Bornholdt and Sneppen (2014) argues that cryptocurrencies are prone to similar effects of competition as new exchanges and currencies are introduced into the market. However, with its large levels of volatility, a low number of daily transactions, and relatively small trading volume, Bitcoin and other competing cryptocurrencies do not yet share the characteristics of sovereign currencies. As a result, their exchanges can be looked upon as having more similarity to equity-based exchanges offering access to pre-trade transparent liquidity than those that trade currencies. Therefore, much of the exchange-based discussion for cryptocurrencies draws on our knowledge of equity markets. The cryptocurrency market resembles current equity markets in that is consists of a series of exchanges. This chapter investigates the effects of increased competitive market fragmentation in the cryptocurrency market and tests whether equity market theories surrounding price discovery, such as those based in rational expectations theory and the efficient market hypothesis, are applicable.

Testing price discovery in cryptocurrency markets becomes more important as cryptocurrencies begin to play a larger role in investment portfolios. Briere, Oosterlinck, and Szafarz (2015) test Bitcoin's contributions to a diversified portfolio. They find that Bitcoin contributes abnormally high returns to the investment portfolio, but also adds to its volatility. However, given its lower correlation with other assets, Bitcoin contributes significantly to portfolio diversification, even at levels as low as 3%.

Decentralised currencies, particularly cryptocurrencies, have the potential to significantly alter the landscape of future financial and retail market operations. Most notably, they have the potential to streamline the processes currently used to transfer funds. The financial industry is currently investigating the viability of cryptocurrencies, and other forms of virtual currencies, as investable assets.[31] On the other hand, the retail industry is looking into utilising the technology for transactional purposes. Retailers understand that decentralised currency technology is particularly helpful in facilitating cross-border transactions as it has the potential to improve both the speed and cost of the transaction. However, many concerns regarding the efficiency and security of such systems have delayed their wide-spread adoption.

As it stands, most financial market participants have not embraced cryptocurrencies. Due to their limited market share compared to other financial assets, cryptocurrencies currently have a negligible influence on the global economy. However, infrastructural developments demonstrate that it is feasible to use distributed ledgers in order to facilitate peer-to-peer transactions, thus negating the need for an established intermediary. Also, the incorporation distributed ledgers into general investment practices open the door for the development of new investment techniques and strategies, including those that require simultaneous access to multiple sovereign marketplaces.

Investors are beginning to see the potential benefits of cryptocurrencies and are beginning to invest heavily in start-ups looking to further the technology. As of November 2016, $1.4 billion have been invested in digital currency start-ups.[32] R3CEV, for example, is a consortium of forty-two of the largest banks whose goal is to develop blockchain technology further. Another example is the Open Ledger Project, which involves some of the largest names in the computing industry including IBM, Intel, Cisco and the Linux Foundation. The goal of the Open Ledger Project is to foster the deployment and adoption of the distributed ledger technology by focusing on innovation and security. As a result, cryptocurrency markets have experienced numerous substitutionary and competitive market fragmenting events. The focal point of this study, competitive market fragmentation, can have a significant impact on the supply of cryptocurrencies in the market, as well as the stability of the market itself. The empirical study presented in this chapter examines the impact of competitive market

[31] 4 Reasons Why Bitcoin Represents a New Asset Class - Forbes: http://www.forbes.com/sites/laurashin/2016/06/02/4-reasons-why-bitcoin-represents-a-new-asset-class/#1aff43e55ce5

[32] $1.4 Billion Invested in Blockchain, says PwC Executive - Bitcoin: https://news.bitcoin.com/1-4-billion-invested-blockchain-pwc/

fragmentation on the dissemination of key price adjusting information, specifically, the introduction of new exchanges for facilitating transactions.

4.2 Description of Cryptocurrencies

Cryptocurrencies are a transactive asset classified in the family of digital currencies. However, unlike other digital currencies such as electronic-money (e-money), cryptocurrencies are not simply a digital representation of a sovereign currency. Instead, they represent a new form of currency that maintains its own value and is not supported by any sovereign entity. Figure 4-1 below shows where cryptocurrencies, such as Bitcoin, fall within the taxonomy of digital currencies.

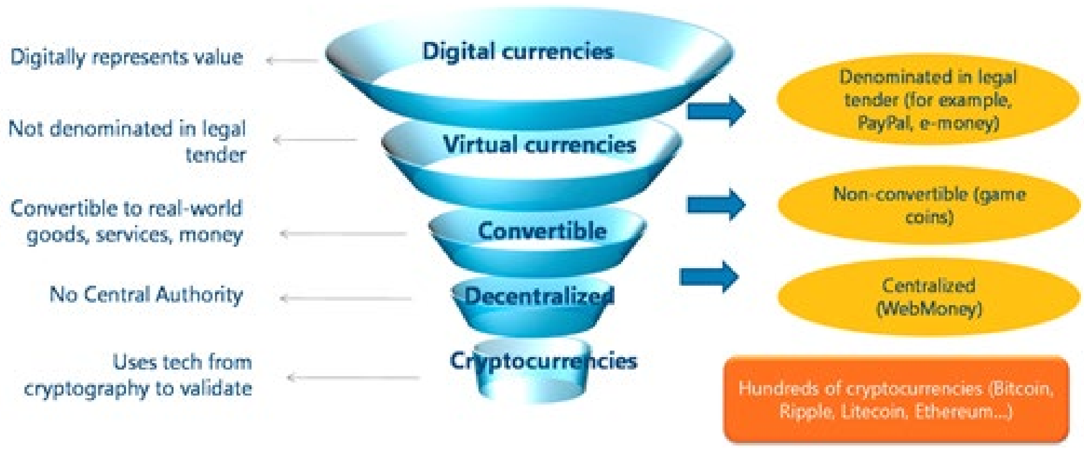


Figure 4-1: Taxonomy of Digital Currencies

Source: (He et al., 2016) (IMF.org)

The term money applies to both physical and electronic forms of currency, with notes and coins representing the former and bank deposits representing the latter. According to the Committee on Payments and Market Infrastructure (CPMI), e-money is a form of digital currency whose value is stored electronically on a device such as a computer chip in a card or a computer hard drive. Similar to bank deposits, the value of e-money is represented by that of the sovereign currency in which the issuing bank transacts. As a result, it can be easily exchanged for fiat money and used in retail transactions. Due to their similarities, the CPMI has categorised the above three forms of payment (cash, bank deposits, and e-money) as 'money' and regards them as the same from a policy and regulatory standpoint (BIS, 2003).[33]

Digital currencies, including cryptocurrencies, do not fall under the category of e-money in the majority of dominions around the world. This is because most regulatory bodies require the value stored to be denominated in and represented by some sovereign currency. However, the majority of digital currencies, and by definition, all cryptocurrencies, maintain their own unit of measure and are exchanged for sovereign-based currency based on the current market exchange rate.

4.2.1 Factors influencing the development of cryptocurrencies

Cryptocurrencies operating non-centralised ledgers, known as distributed ledgers, are a relatively new concept. They are still growing in terms of market adoption as well as from an operational standpoint. This section outlines some of the factors that play a major role in both helping and hindering the widespread use of cryptocurrencies in the market. It begins with a look at the factors that influence the supply of and demand for cryptocurrencies and finishes with a look at the role of regulation in the process.

4.2.1.1 Supply-based factors

Private non-bank institutions have taken a leading role in developing cryptocurrencies other digital currencies.[34] Therefore, they are the main source of substitutionary fragmentation in cryptocurrency markets. Banks have only recently begun to fund digital currency start-ups in order to maintain a footing in the market. They are also motivated by a desire to provide services to their customers that provide access to the digital currency market; though admittedly the motivation behind their involvement can vary.

Financial motives imply that banks are interested in implementing the technology in order to reap the financial rewards. By issuing the currency, the bank can not only profit its issuance but also on the resulting capital gains earned by maintaining a positive position in the currency. Finally, maintaining the ledger and facilitating transactions results in newly earned transaction fees. If the motivation is non-financial, firms may develop cryptocurrencies to gain a better understanding of their operations. This served as a 'warm-up' for future events where the

[33] For a detailed explanation of this perception of "singleness" in relation to central and commercial bank money (mainly based on the confidence that banks have the ability to convert their sight liabilities into central bank money upon demand), see CPMI, *The role of central bank money in payment systems*, August 2003.

[34] A non-bank in this report is defined as "any entity involved in the provision of retail payment services whose main business is not related to taking deposits from the public and using these deposits to make loans": CPMI, *Non-banks in retail payments*, September 2014.

technology becomes more widespread. Previous experience makes it easier for the institutions to adapt and maintain a competitive strategic position in the market.

Unlike the equity market, digital currencies are also subject to a second form a fragmentation, substitutional fragmentation. As of January 2017, there are more than 680 cryptocurrencies available for purchase through online platforms (exchanges) but only 10 that have market capitalisations over $10 million (USD). Of the 680 available cryptocurrencies, the vast majority are nearly identical and only differ in terms of accessibility and user base. They represent events of substitutionary fragmentation offering investors only modified access to existing products. As there is no underlying intrinsic value to a unit of cryptocurrency, $1USD of currency A should be no different from $1USD of currency B. Therefore, cryptocurrency markets are subject to the influence of competing currencies offering nearly identical services. Equity based assets, on the other hand, differ widely in terms of the underlying assets they represent, the industry they are in, the services they provide, the payments they entitle the holder to, and the regulations to which the underlying company must adhere.

From both an exchange and currency standpoint, fragmentation can hinder a firm's ability to achieve the critical amount of transactional volume necessary to maintain operations. Much like with dark pools (Majtyka et al., 2015), cryptocurrencies and the exchanges in which they trade may need to consolidate in order to develop a more robust user base.

The ability to scale cryptocurrencies' technology while maintaining operational efficiency has not yet been realised. As a result, the retail payment systems maintain dominance in the market for exchange. While many cryptocurrency services can maintain efficiency regarding the speed of transactions, it is unknown if these speeds will be maintained when the project is scaled upward. Also, the computing power and electrical energy required to complete a small number of transactions is not insignificant and can be a potential source of strife as cryptocurrencies continue to grow. However, as technology improves, so does the efficiency of the system.

The levels of anonymity within some digital currency programs can also be present roadblocks when developing or expanding the service. Institutional participants may find it difficult to provide these services while still adhering to regulations. The Anti-Money Laundering and Counter-Terrorism Financing Act (AML/CTF) requires institutions to report suspicious transactions and overseas currency flow which, with the level of anonymity present within the distributed ledger, can introduce difficulties in identifying suspicious parties.

Finally, developments in security can either encourage or discourage the implementation of digital currency schemes. Operators of distributed ledgers must work towards maintaining the accuracy of the ledger. Discrepancies between versions of the distributed ledger can lead to its collapse if not resolved as customers can no longer trust that their money is 'safe'. Distributed ledgers are also subject to manipulation which, if not identified, can lead to the theft of virtual currency units from 'wallets'.[35]

4.2.1.2 Demand-based factors

If companies want to further the adoption of digital currencies in the market, they must provide users with incentives over traditional retail services. In lieu of recent events, security is one of the top concerns of users interested in digital currency. The recent theft of over $78 million (USD) in Bitcoin from Bitfinex in Hong Kong has raised concerns over the safety of digital currency 'deposits'. Users, however, can also lose access to funds if they forget the information necessary to access their 'wallets'. Unfortunately, the use of 'wallets' is also not without risk as the party/parties responsible for maintaining the ledger can also be subject to attacks and other phenomena that can lead to the loss and corruption of data.

One way in which digital currencies aim to compete with the traditional retail process is through cost. Some digital currencies offer discounted transaction fees to encourage their use. They can afford to do so as they are not subject to the same operational and infrastructure expenses as traditional retail systems. Other programs reward users for participating in the clearing process as well as maintaining a copy of the ledger itself. Rewards vary but are typically in the form of new currency units which can be immediately sold or held in order to earn additional capital gains.

Block size limits are also influencing how users approach digital currencies. With Bitcoin, for example, each block size contains 1MB of transactional data. New blocks form approximately every 10 minutes; however, it takes less than that amount of time to create 1MB worth of transactions. Market participants must now compete in order to transact within the 1MB limit or face higher prices resulting from the increased demand for the currency.

Recently, the 1MB block size has divided Bitcoin users and market facilitators. Market facilitators, otherwise known as data-miners, are responsible for maintaining the distributed ledger and aid in the clearing process. Users argue that fees resulting from maintaining the

[35] Bitcoin worth $78 million stolen from Bitfinex exchange in Hong Kong, The Guardian: https://www.theguardian.com/technology/2016/aug/03/bitcoin-stolen-bitfinex-exchange-hong-kong

current block size will hinder the introduction of low-value transactions, a staple of the retail industry. Increasing the block size may, however, give larger data miners a competitive advantage over their smaller counterparts and result in the centralisation of clearing services. This introduces the potential for collusion amongst market facilitators as a few large data-miners can potentially conspire to manipulate the distributed ledger (Bonneau, 2015).

Having a system that is easy to use is also a significant factor in terms of the client-side adoption of digital currency schemes. How easy is the process? Can it be used for various purposes throughout the day? The final questions recognise that versatility is important to the adoptions of cryptocurrencies as customers tend to look for the 'one-stop-shop' that caters to all of their needs. This is currently one of the key areas that digital currency providers are focusing on as it not only improves adoptions rates but encourages customers to continue to use the service and incorporate it into their daily lives.

Users who do not immediately liquidate their holding in digital currencies in favour of a sovereign currency face the risk capital losses. Bitcoin is regarded as an unstable currency whose value fluctuates significantly throughout the day. It is also subject to flash crashes and waves of sentiment, both positive and negative (Bornholdt & Sneppen, 2014). This level of volatility can discourage users who want to use digital currencies for transactional purposes while simultaneously encouraging speculative investment (Baur & Dimpfl, 2019). The academic and finance communities are still uncertain as to the effect that widespread adoption may have on volatility.

4.2.1.3 Regulation

Future developments in the regulatory environment surrounding virtual currencies may significantly influence the adoption of virtual currencies technologies from both a supply and demand standpoint. As virtual currencies are a fairly new construct, they do not easily fit within existing policies and regulations. Their cross-border nature and lack of a central issuing authority pose major barriers in the formulation of realistic and effective policies.

Of particular interest to any government is the potential for virtual currencies to facilitate illegal activities. In 2014, the Financial Action Task Force (FATF) distributed a report stating that *"convertible virtual currencies that can be exchanged for real money or other virtual currencies are potentially vulnerable to money laundering and terrorist financing"*.[36]

[36] Financial Action Task Force, *Virtual Currencies: Key Definitions and Potential AML/CFT Risks*, June 2014.

The following are the key areas that regulators are targeting most in order to influence the development of new policies He et al. (2016):

> *Awareness* – Use education and awareness to influence the development and adoption of virtual currencies from an institutional and retail standpoint, respectively.
>
> *Targeted Regulation* – Limit regulation to a particularly important subset of participants, notably those that exchange virtual currencies for sovereign ones. This would shed light and concentrate efforts on the stage of the transaction process that is most likely to result in or facilitate criminal activity.
>
> *Application of Existing Regulations* – Some of the existing regulations and policies may be applied to virtual currencies; however, their efficacy and applicability must first be assessed.
>
> *Prohibition* – Ban any or all of the following: the formation of virtual currency exchanges, the use of virtual-currency based transactions, virtual currency exchanges, the ability for retailers to accept virtual currencies.

4.3 Existing Literature

There is a recent limited but growing cryptocurrency research literature. Some studies investigate the validity of Bitcoin and other cryptocurrencies as a replacement for traditional fiat currency (Lots & Vasselin, 2013). Other studies focus on price discovery and volatility transmission (Eun & Sabherwal, 2003; Pascual et al., 2006). Others study the price dynamics and their relationship to the market structure of Bitcoin markets (Brandvold et al., 2015; Fink & Johann, 2014). This study extends this latter body of research and investigates the price dynamics and market microstructure. Like the empirical study reported in Chapter 3, the current chapter's empirical study investigates the relationship between competitive market fragmentation and the price discovery process but in this case related to cryptocurrency markets. The goal is to determine again if fragmentation is positively or negatively related to the market's ability to gather and impound into the price of the asset all relevant price adjusting information.

A key contribution of this study is to test the applicability of equity-based research surrounding rational expectations theory and the efficient market hypothesis to a new asset class, cryptocurrencies. See Section 3.2.1 for a detailed analysis of competitive market fragmentation in pre-trade transparent exchanges. In summary, the results surrounding the benefits of fragmentation within lit order books are mixed. Recent studies find that fragmentation is beneficial to the price discovery process (R. H. Battalio, 1997; B. Boehmer & Boehmer, 2003; Colliard & Foucault, 2012; Foucault & Menkveld, 2008). However, benefits observed across the consolidated global order book come at the expense of degradation to the local exchange and retail investors (Degryse et al., 2015; Gresse, 2017). The results of the empirical study reported in Chapter 3 support these findings of prior research. The issue this chapter addresses is whether or not these findings also extend to cryptocurrency markets. The following review of literature helps inform testable hypotheses that are tested in this study.

Substitutionary Fragmentation

Bornholdt and Sneppen (2014) and Baur, Dimpfl, and Kuck (2018) show that Bitcoin, as a cryptocurrency, contains no characteristics that noticeably differentiate it from other cryptocurrencies. They argue that the perception of its value over other currencies stems from a herd mentality where users tend to centralise themselves around established market constructs. As a result, Bitcoin and other cryptocurrencies are susceptible to being replaced due to the presence of substitute products.

Furthermore, as the number of coins in a currency can be constant, or grow at a constant rate, the number of competitive currencies introduced into the market is more sporadic. Cloning, adjusting, or introducing substitute cryptocurrencies contains few barriers to entry. However, as more currencies are introduced, they not only compete for market share but memory across computers and servers worldwide. Remember that these currencies operate using a distributed ledger and, as a result, require external support to maintain the ledger as well as settle and clear transactions. Non-trading participants, those users that help facilitate the trading process, will, therefore, be incentivised to move to the market that is most active or can best compensate them for their participation (Bornholdt & Sneppen, 2014). This results in increased market share for new currencies while older, less traded currencies, become forgotten and exit the market. For more information on substitutionary fragmentation in cryptocurrency markets refer to the discussion in Section 2.4.2.

Competitive Fragmentation and Price Discovery

Several studies focus on pricing dynamics and their relation to the microstructure of Bitcoin markets. Section 2.2.4 discusses these findings in detail; however, the results are also summarised below. Fink and Johann (2014) conduct a study into pricing dynamics and their relation to the microstructure of Bitcoin markets. Using a vector-error-correction-model (VECM) in conjunction with Gonzalo and Granger's (1995) Component Share (CS) and conclude that, before the bankruptcy of Mt. Gox, nearly all exchanges have at least a 10% level of influence on the prices of their competitors. Mt. Gox (USD) noticeably exceeds 10% level and is identified price leader. Being the market leader in transactional volume at the time this result conforms to theory by Joel Hasbrouck (1995) who argues that the dominant exchange is the source of the majority of price forming information. Brandvold et al. (2015) also focus on price discovery in Bitcoin exchanges. Using a multivariate version of Hasbrouck's (1995) Information Share (IS), they find partial support for the results presented by Fink and Johann (2014). They find that the dominant exchange, Mt. Gox, is the price leader.

Vs Fiat Currency

Some Bitcoin papers focus on the validity of Bitcoin and other cryptocurrencies as a replacement for traditional fiat currency. Lots and Vasselin (2013) argues that. given sufficiently low transaction costs, digital currencies could ultimately replace traditional fiat currencies and lead to their obsolescence. However, some studies take an opposing standpoint. Yermack (2015) notes that Bitcoin is not suitable to be a currency because of the instability of its price.

4.4 Problem, Contribution and Hypotheses

Many Bitcoin (BTC) exchanges allow for trading across multiple fiat currencies. However, they operate separate order books for each fiat currency in which investors can transact. Exchanges also restrict customers to the order books which use their local currency. This results in the fragmentation of BTC investors into pools based on their home currency as identified by the country in which they are currently a resident. This study investigates two fiat based, USD and Euro, BTC markets determine if they react similarly to competitive market fragmenting events. This study investigates RQ3 by testing the applicability of equity-based research principles, such as rational expectations theory and the efficient market hypothesis, to instances of competitive market fragmentation in a relatively new asset class, cryptocurrencies.

Pagano (1989) argues if two similar exchanges exist with unequal trading costs, some investors will concentrate on one exchange while others migrate to the alternative exchange. Chowdhry and Nanda (1991) extend the work of Kyle (1985) and find that adverse selection risk increases along with an increase in the number of exchanges listing a particular asset. Glosten and Milgrom (1985) deduce that increased participation from informed competitive traders is proportional to bid-ask spreads due to adverse selection. The increase in adverse selection risk results from increased competitive market fragmentation and hinders a market's ability to formulate accurate prices (Chowdhry & Nanda, 1991; Madhavan, 1995). Also, Hasbrouck (1995) concludes that, for those shares whose primary listing is on the New York Stock Exchange (NYSE), the primary exchange is responsible for over 90% of price discovery when compared to regional satellite exchanges on which the asset is cross-listed. However, any informed activities that leave the market take with them some permanent price-adjusting information. This leads to the first two hypotheses for the study:

H4-1: When multiple exchanges offer the ability to transact in the same cryptocurrency asset, price adjusting information is spread across multiple cryptocurrency exchanges and does not originate from a single source.

H4-2: The market share of a cryptocurrency exchange is positively related to the informational content of prices on said exchange.

When there exists a greater proportion of large liquidity traders who can simultaneously access multiple exchanges, markets experience an increase in volume but also a decrease in the informativeness of prices (Chowdhry & Nanda, 1991; Madhavan, 1995). Greater fragmentation affords informed investors the ability to more easily conceal their trades from investors wishing to take advantage of their superior information Madhavan (1995). This results in the migration of critical price-adjusting information across exchanges and leads to the following hypothesis.

H4-3: Market fragmentation across cryptocurrency exchanges is positively related to the informational content of prices on an exchange.

Local exchanges, those that operate within the same country as a particular order book currency, will contain more price discovery than foreign exchange. Noronha et al. (1996) find that informed trading increases following international cross-listing, leading to more efficient and informative prices. However, the primary market is still believed to provide the majority of price disseminating information. Ultimately, price discovery occurs in the primary domestic exchange (Su & Chong, 2007) which leads to the final hypothesis for the study:

H4-4: Cryptocurrency exchanges transacting in USD (Euro) contribute more information to USD (Euro) cryptocurrency transactions than Euro (USD) cryptocurrency transactions.

4.5 Data

This chapter utilises tick level transaction data and order book data obtained from CoinMarketCap. It also references data from BitcoinCharts.com for supporting information regarding market totals. Bitcoin (BTC) data is chosen as it is the largest and most liquid cryptocurrency with regards to market capitalisation and trading volume, respectively. BTC is also the oldest and most recognisable cryptocurrency whose name is used as an eponym for all cryptocurrencies.[37]

BTC data is collected from January 1st, 2017 to March 31st, 2019. The data is not only recent at the time of the writing of this thesis, it also corresponds to a highly liquid period of the BTC market. This allows for the use of more granular data in constructing the necessary variables due to the frequency of transactions.

BTC data is collected for the following six exchanges: Bitfinex, Bitstamp, Coinbase, Exmo, Gemini and Kraken. These exchanges are among the most liquid BTC exchanges with regards to trading volume. Both USD and Euro data is used as they represent the two most active BTC markets when we consider the fragmentation of investors by their respective fiat currency. Bitstamp, Exmo, and Kraken operate both USD and Euro order books while Bitfinex, Coinabase and Gemini only allow for USD trading. During the study period, these markets represent 81% and 74% of total BTC trading volume in USD and Euro, respectively (see Table 4-1).

4.5.1 Transaction Data

Millisecond time-stamped data is used to calculate the various dependent and independent variables used in the analysis. The following information is required for each transaction:

1. Currency – An identifier that indicates the currency in which the trade occurs
2. Date – The date of the transaction
3. Time – The time of the transaction (accurate to the nearest millisecond)
4. Exchange - The venue from which the transaction originates
5. Price – The price per unit
6. Quantity –The number of units in the transaction

4.5.2 Quote Data

The following information is collected on a 1-minute basis for each order book in order to calculate bid-ask spreads:

[37] People refer to cryptocurrencies as Bitcoin akin to the way in which they use Kleenex when referring to facial tissue, or Q-tips when referring to cotton swabs.

1. *Currency* - An identifier that indicates the currency in which the trade occurs to which the quote pertains
2. *Date* – The date of the current order book snapshot
3. *Time* – The time of the current order book snapshot
4. *Exchange* – The exchange that advertises the quotes
5. *Bid Price* – The price at which investors can sell the asset
6. *Ask Price* – The price at which investors can purchase the asset

4.6 Methodology

This section introduces the methods used to conduct the study. Independent and dependant variables are calculated using a combination of SAS, Excel and custom C++ code. SPSS is used to perform the final regression analysis. The following subsections provide further detail regarding the variables and regression analyses used to test the hypothesis outlined in section 4.4. Section 4.6.1 introduces the methods used to calculate price discovery, the dependent variable. Section 4.6.2 discusses independent variables. Section 4.6.3 discusses the regression models used to test the hypotheses. Section 4.6.4 tests the regression assumptions to ensure the validity of the regression results.

4.6.1 Measuring Price Discovery

This section outlines the key measure of price discovery used in this chapter. We use SAS to calculate the dependant variables on raw transaction price and order book data that was first processed using custom C++ code. The measure is calculated for each exchange in the study for each trading day. Exchange prices, and subsequent returns, are calculated on 5-minute intervals. This follows the findings of Anderson (2000) who suggests that this time frame is short enough to account for the granularity of the data but long enough to avoid capturing a meaningful number of observations and minimise noise. The construction of the price discovery metric follows the approach modelled by de Jong (2001) and applied to the cryptocurrency market by Brandvold et al. (2015). This multivariate time-series model is designed to measure the degree to which an exchange contributes permanent price adjusting information to a market comprised of several exchanges.

Similar to the information share (Hasbrouck, 1995) and component share (Gonzalo and Granger, 1995) price discovery measures discussed in Section 4.5.1, de Jong (2001) assume that prices are comprised of the efficient price and an idiosyncratic noise component. This allows a single, unobserved, efficient price to be the basis for the prices found on each exchange with deviations from that price being a result of exchange specific factors. Separating idiosyncratic factors from the efficient price was first introduced by Hasbrouck (1995).

Exchanges and markets are defined in order to measure price discovery. An exchange consists of a single order book where investors can buy and sell BTC. A market refers to all other exchanges (order books). Price discovery is therefore calculated for n exchanges across m markets where $n=m$.

Section 4.5 states that order books operate separately for each fiat currency and that customers rarely have access to order books for fiat currencies outside of their local currency. Therefore, price discovery measures are calculated separately for USD and Euro markets. This not only helps differentiate between subsets of investors but also eliminates the risks associated with exchange rates and cross-currency transactions. As a result, there are $n=6$ USD exchanges and $n=4$ Euro exchanges.

Let P be a vector of prices where P^e is a vector of exchange prices and P^m is a vector of market prices. Also, let U be a vector of idiosyncratic components with U^e and U^m referring to the idiosyncratic components for the exchange and the market, respectively. Element i of P^e and U^e refer to exchange i while element j of P^m and U^m refer to market j. Finally, denote P^* as the efficient price.

If $p^e = lnP^e$, $u^e = lnU^e$ and $p^* = lnP^*$ the n-vector of exchange prices is

$$p_t^e = p_t^* + u_t^e \tag{25}$$

and the m-vector of market prices is

$$p_t^m = p_t^* + u_t^m \tag{26}$$

If p^* is a random walk it is assumed that you cannot predict the efficient price (Hasbrouck, 1995). Since prices across all exchanges and markets are centred around the same efficient price, p^*, by design the prices are cointegrated.

Changes in the efficient price from period t-1 to period t are defined as

$$r_t = p_t^* - p_{t-1}^* \tag{27}$$

The model assumes that unconditional serial covariances are stable across r_t, u_t^e and u_t^m. This allows for the following definitions where ψ, γ_l and Ω are (n x 1) matrices:

$$E[r_t^2] = \sigma^2 \quad (28a)$$

$$E[r_t u_{it}^e] = \psi_i \quad (28b)$$

$$E[r_t u_{jt}^m] = \psi_j \quad (28c)$$

$$E[r_t u_{i,t+1}^e] = \gamma_{li},\ l \geq 0 \quad (28d)$$

$$E[r_t u_{j,t+1}^m] = \gamma_{lj},\ l \geq 0 \quad (28e)$$

$$E[r_t u_{i,t-k}^e] = 0,\ k > 0 \quad (28f)$$

$$E[r_t u_{j,t-k}^m] = 0,\ k > 0 \quad (25g)$$

$$E[u_{it}^e] = \Omega^e \quad (28h)$$

$$E[u_{it}^e u_{jt}^m] = \Omega,\ i = j \quad (28i)$$

$$E[u_{i,t-k}^e] = 0,\ k \neq 0 \quad (28j)$$

$$E[u_{it}^e u_{j,t-k}^m] = 0,\ k \neq 0 \quad (28k)$$

de Jong et al. (2001) define r_t as the price adjusting component that leads to changes in the efficient price, p^*. Since r_t is the return corresponding to changes in p^*, and p^* is a random walk, r_t is serially uncorrelated.

p is the only variable that can be observed. Therefore, it is critical in helping calculate the measure of price discovery. Let

$$y_{it} = p_{it} - p_{it-1} = p_t^* + u_{it} - p_{t-1}^* + u_{it-1} = r_t + u_{it} - u_{it-1} \quad (29)$$

and let the vectors of prices for exchanges and markets be

$$Y_t^e = \iota r_t + u_t^e - u_{t-1}^e \quad (30a)$$

$$Y_t^m = \iota r_t + u_t^m - u_{t-1}^m \quad (30b)$$

ι is a vector of ones of size n. Using the definitions listed in Equations (27a) to (27k) the serial covariances of Y_t are

$$E[Y_t Y_t'] = \sigma^2 \iota\iota' + \iota\psi' + \psi\iota' + 2\Omega \quad (31a)$$

$$E[Y_t Y'_{t-1}] = -\psi\iota' - \Omega + \gamma\iota' \tag{31b}$$

$$E[Y_t Y'_{t-2}] = -\gamma\iota' \tag{31c}$$

The covariance between exchanges and their markets are key to the final results and are defined as the covariance between and element and its counterpart in vectors Y^e and Y^m, respectively. Given this information and Equations (31a) to (31sc)

$$E[y_{jt} y_{it}] = \sigma^2 + 2\omega_{ij} + \psi_j + \psi_i \tag{32a}$$

$$E[y_{jt} y_{i,t-1}] = -\omega_{ij} - \psi_j + \gamma_j \tag{32b}$$

$$E[y_{jt} y_{i,t-2}] = -\gamma_j \tag{32c}$$

The first-order autocorrelation for exchanges is defined as

$$\rho_{1,ii} = \frac{-(\omega_i^e + \psi_j - \gamma_j)}{\sigma^2 + 2(\omega_i^e + \psi_i)} \tag{33}$$

The covariance between the new price adjusting information and the idiosyncratic component is ψ_i as defined in (25b) and (25c). The larger the value of ψ_i the stronger the signal of price adjusting information originating from that exchange.

Finally, the information share attributable to a single exchange is defined as

$$IS_i = \frac{(\sigma^2 + \psi_i)\pi_i}{\sigma^2} = \pi_i\left(1 + \frac{\psi_i}{\sigma^2}\right) \tag{34}$$

where π_i is the activity share of an exchange and is defined by the proportion of transactions taking place in the exchange relative to the entire market. The sum of all π_i equals 1. By imposing the rule that $\pi'\psi = 0$ the sum of all information shares across all exchanges sum to 1.

4.6.2 Independent Variables

This following section lists the series of independent variables used in the study, some of which are key regressors relating to fragmentation and are used to test the hypotheses while the remainder are control variables. A combination of custom C++ code and Excel are used to calculate the variables contained in this section.

4.6.2.1 Fragmentation Measures

This section discusses methods used to test the impact of fragmentation on the price discovery process. We begin by measuring the level of competition among BTC exchanges. Separate fragmentation figures are calculated for USD and Euro exchanges. Similar to Equation 7 in

Chapter 3, fragmentation is measured using the Herfindahl-Hirschman Index (HHI). It follows previous research (Buti et al., 2017; Degryse et al., 2015; Gresse, 2017) and measures the extent to which trading activity concentrates around a single exchange. As a result fragmentation for order books using currency *c* at time *t* ($Frag_{c,t}$) is measured as follows:

$$Frag_{c,t} = 1 - \sum_{v=1}^{n} MS_{c,t,v}^2 \tag{35}$$

where *c* represents either the USD or Euro order books,

t is the observation day,

v represents a particular exchange or order book,

MS_v^2 is the squared market share of trading venue v, measured by the number of BTC traded in venue v when compared to the market as a whole.

1-HHI is used in order to allow the measure to more obviously measure fragmentation and an increase in *Frag* corresponds to increased fragmentation in the market for any particular stock.

Next, the study focusses on trading activity within a single exchange. Due to the increasing popularity of Bitcoin the market is no longer consolidated around a single exchange. Instead, many exchanges offer order books in which investors can buy and sell BTC. Trading activity is measured for a single exchange using the market share of trading volume attributable to each exchange (*MS*).

$$MS_{c,i,t} = Vol_{c,i,t} / Vol_{c,t} \tag{36}$$

where *c* represents a particular currency,

t is the observation day,

$Vol_{c,i,t}$ is the daily transaction volume, in currency *c,* for exchange *i* at time *t,*

$Vol_{c,t}$ is the total daily volume for all exchange in currency *c* at time *t*.

4.6.2.2 Control Variables

The regressions control for the following factors: volatility, bid-ask spread, and total daily volume. These concepts are defined and measured as discussed below and the measures are calculated separately for order books of each currency (USD and Euro):

1. **Volatility $(\sigma)_{i,t}$** – Volatility measured by the standard deviation of returns over the course of a trading day, *t*. It is calculated as follows:

i. $r_{i,t,s} = Ln(\frac{Mi_{,t,s}}{M_{i,t-1},s})$ (37)

where *i* represents a particular exchange,

t is the observation day,

s is the time of day t,

$r_{i,t,s}$ is the logarithmic return between 5-minute snapshots,

$Mi_{,t,s}$ is the current midpoint of the best bid-ask spread,

$M_{i,t-1}, s$ is the midpoint of the best bid-ask spread from the previous snapshot.

ii. $\overline{r_{i,t}} = \frac{\sum_{s=1}^{S} r_{i,t,s}}{S}$ (38)

where i represents a particular exchange,

t is the observation day,

s is the time of day t,

$r_{i,t,s}$ is the logarithmic return between 5-minute snapshots,

$\overline{r_{i,t}}$ is the average return over the course of the trading day,

S is the number of 5-minute snapshots over the course of the trading day.

iii. $\sigma_{i,t} = \sqrt{\frac{\sum_{s=1}^{S}(r_{i,t,s} - \overline{r_{i,t}})^2}{S-1}}$ [38] (39)

where i represents a particular exchange,

t is the observation day,

s is the of day t,

$r_{i,t,s}$ is the logarithmic return between 5-minute snapshots,

$\overline{r_{i,t}}$ is the average return over the course of the trading day,

S is the number of 5-minute snapshots over the course of the trading day.

2. **Bid-Ask Spread (BASp)$_{i,t}$** – Average quoted spread for exchange *i* over the course of a trading day, *t*. It is calculated as follows:

i. $QS_{i,t,s} = \frac{P_{i,t,s}^{BestAsk} - P_{i,t,s}^{BestBid}}{P_{i,t,s}^{BestAsk}}$ (40)

[38] We use S-1 as this is a sample measure because it is not possible to have all possible outcomes.

where i represents a particular exchange,

t is the observation day,

s is the time of day t.

${P_{i,t,s}}^{BestAsk}$ is the best available ask price,

${P_{i,t,s}}^{BestBid}$ is the best available bid price.

The bid-ask spread is calculated every 5-minutes of the day and averaged over the course of a trading day.

3. **Total Volume (Vol)$_{\mathbf{i,t}}$** – Total volume is the total Bitcoin trading volume on exchange i over the course of a single trading day, t, measured in the transaction's respective currency. It is calculated as follows:

i. $$Vol_{i,t} = \sum_{r=1}^{N} NumShares_{r,i,t} * Price_{r,i,t} \quad (41)$$

where i represents a particular exchange,

t is the observation day,

r is the current transaction,

N is the total number of transactions over the course of trading day t,

$NumShares_{r,i,t}$ is the number of shares in transaction r,

$Price_{r,i,t}$ is the price at which transaction r took place.

4. **Average Trade Size (AvgTS)$_{\mathbf{i,t}}$** – The average size of a transaction on exchange i over the course of a single trading day, t. This result is reported in the currency in which the transaction took place[39]. It is calculated as follows:

i. $$AvgTS_{i,t} = \frac{Vol_{i,t}}{NumTrades_{i,t}} \quad (42)$$

where i represents a particular exchange,

t is the observation day,

[39] For control variables 1-4 we use the LN() of the original value. Logarithms convert changes in variables into percentage changes and this figure will provide a more descriptive result as it will scale down the changes amongst stocks.

$Vol_{i,t}$ is the total daily trading volume, measured in the exchange's respective currency,

$NumTrades_{i,t}$ is the total daily number of trades on exchange i.

4.6.3 Panel Regression

The approach to the panel regressions follows the process outlined in Chapter 3. The base for the regression formula is:

$$L_{i,t} = b_0 + b_1 Frag_{i,t} + b_2 MS_{i,t} + b_3 ln\sigma_{i,t} + b_4 lnBASp_{i,t} + b_5 lnVol_{i,t} + b_6 AvgTS_{i,t} + \mu_{i,t} \quad (43)$$

where *Frag and MS* refer to the aforementioned measures of fragmentation and the remainder refer to control variables for volatility (σ), bid-ask spread (*BASp*), total volume (*Vol*) and average trade size (*AvgTs*).

The regression model is extended to include the entity and time fixed effects. The extended model is as follows:

$$L_{i,t} = \alpha_i + \gamma_t + b_1 Frag_{i,t} + b_2 MS_{i,t} + b_3 ln\sigma_{i,t} + b_4 lnBASp_{i,t} + b_5 lnVol_{i,t} + b_6 AvgTS_{i,t} + \mu_{i,t} \; . \quad (44)$$

Regression results are calculated using SPSS. Similar to Chapter 3, quarterly time dummy variables are used to control for events that affect each exchange over a quarterly time period. Also, exchange dummy variables are used to capture events that are unique to each exchange but remain constant over time. Refer to Sections 3.5.3 for a detailed discussion into the construction of the regression formula including all time and entity fixed effects.

4.6.4 Regression assumptions

In order to draw valid conclusions from the results of the fixed effects panel regression the data must fulfil the following four assumptions: normality, linearity, homoscedasticity, and multicollinearity. Testing of these assumptions is detailed below along with empirical measures. See Section 3.5.3 for detailed information on how each test is conducted.

4.6.4.1 Normality

Linear regression assumes that the variables have normal distributions. Non-normally distributed data can distort relationships and significance tests. Normality tests are conducted on both the individual variables as well as the resulting model itself.

Panel A: Bitstamp ***Panel B: Kraken***

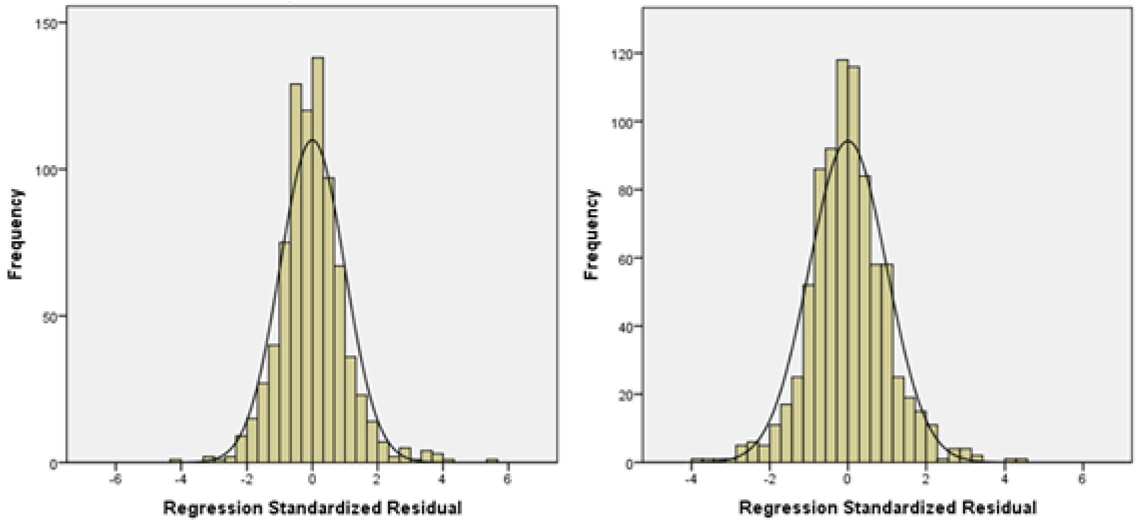


Figure 4-2: Distribution of Dependent Variables

The residuals for the dependent variables are graphed. The test is performed on all independent and dependent variables. However, a subset of the results are presented in the section due to redundancy in the outcomes. Figure 4-2 shows the distribution of the IS residuals. Panel A contains the results from the Bitstamp exchange while Panel B displays results from Kraken. Both panels convey results from USD order books. There is a clear adherence to the assumption of normality, though the relationship is not perfect.

Figure 4-3 support the normality results in Figure 4-2. As the fitted line is not perfectly linear, Figure 4-3 also shows that there is a slight deviation from normality. Though the deviation is not significant enough that the assumption test fails.

Panel A: Bitstamp *Panel B: Kraken*

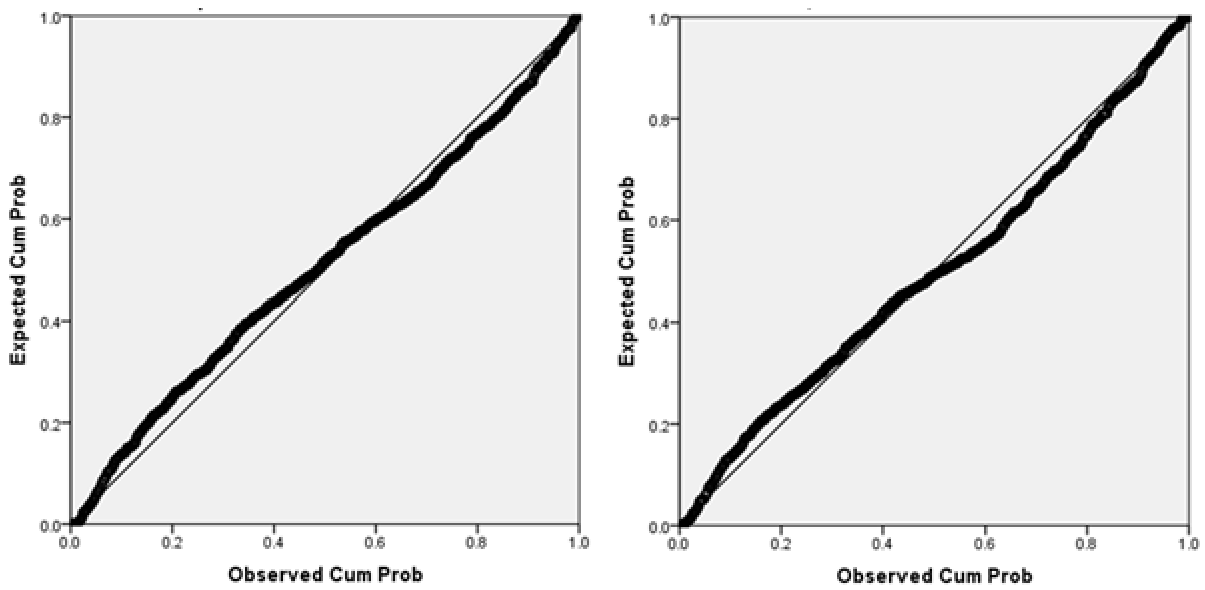


Figure 4-3: Normal Probability Plots

4.6.4.2 Linearity

Figure 4-4 contains the standardised residual versus predicted value plots for Bitstamp (USD) and Kraken (USD) in Panels A and B, respectively. The residual plot pattern conveys a reasonably linear relationship. Therefore, the linearity assumption holds.

Panel A: Bitstamp *Panel B: Kraken*

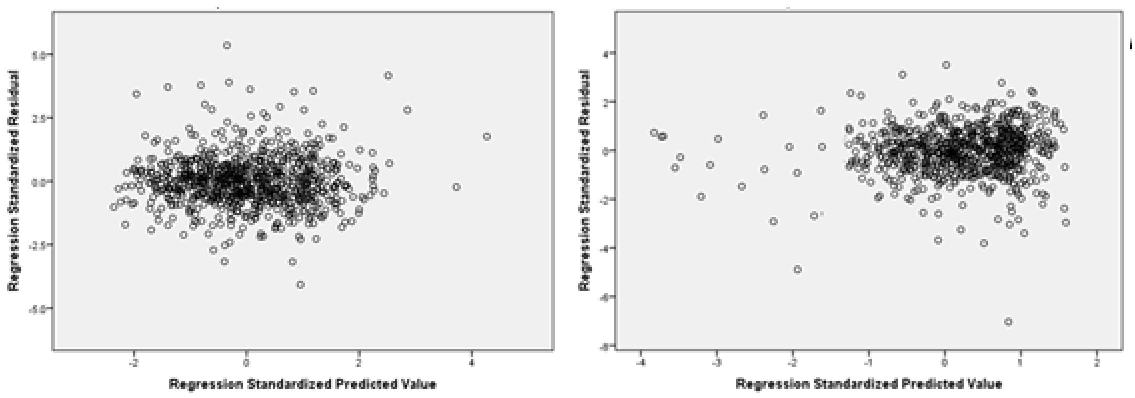


Figure 4-4: Standardised Residuals versus Predicted Values

4.6.4.3 Homoscedasticity

Figure 4-4 also provides support for the homoscedasticity assumption. The variance in the residuals does not change with different values of the predicted value. The variability of the results contained within the plots remains constant.

4.6.4.4 Multicollinearity

Figure 4-5 contains information on the variance inflation factors (VIFs). They are the result of regressing one independent variable against the remaining independent variables. Panel A contains the VIFs from a regression on *Frag* while Panel B contains the VIFs from a regression on *MS*. Once again, repeat results are omitted due to redundancy. VIF values of 2.053 for *MS* and 2.855 for *Frag* indicate that the level of multicollinearity among the key regressors is minimal. However, some of the control variables indicate moderate to high levels of multicollinearity given by the VIFs that exceed 3 and 5, respectively.

Table 4-1: Variance Inflation Factors

Panel A: Frag

	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
MS	0.487	2.053
LN Volatility	0.333	3.004
LN Spread	0.175	5.729
LN Volume	0.154	6.489
LN AvgTS	0.198	5.06

Panel B: MS

	Collinearity Statistics	
	Tolerance	VIF
(Constant)		
Frag	0.35	2.855
LN Volatility	0.111	9.048
LN Spread	0.181	5.537
LN Volume	0.118	8.486
LN AvgTS	0.213	4.699

Note. This table contains information on the variance inflation factors (VIF). The results are collected from performing an OLS regression on the previously dependent variables Frag and MS located in Panels A and B, respectively. Note that dummy variable VIF values are excluded from the table.

4.7 Results

This section presents the results of the study. Initially, descriptive statistics are presented to profile the data and measures of the study. Next, the section presents the main result tables testing the hypotheses outlined earlier. The results are discussed before drawing key insights and conclusions from the empirical study of cryptocurrency markets.

4.7.1 Descriptive Statistics

This section presents the descriptive statistics for Bitcoin markets throughout the study period of January 1 2017 to March 31 2019. Cryptocurrency exchange participants are predominately limited to using their home currency in transactions. As a result, Euro currency traders are largely isolated from trading with USD currency traders. Therefore, the data presented in this section are split into USD trading and Euro trading categories. Separating the order books allows the study to investigate the effects of fragmentation resulting from changes to the structure of order books, that is, the structure of the market, in which an individual investor can participate. This is an important distinction as Euro traders are less influenced by the structure of the USD Bitcoin market. While the geographical location of the change influences the currencies against which its cryptocurrencies transact, exchanges can decide to construct order books for several currencies. For example, of the six cryptocurrency exchanges used in the study only two, Bitfinex and Gemini, restrict trading to a single currency. Many of the sampled exchanges also allow trading in other cryptocurrencies. However, this study focuses on the oldest and most established cryptocurrency, Bitcoin.

Table 4-2 presents descriptive statistics for Bitcoin transactions, with USD and Euro trade data found in Panels A and B, respectively. Daily transactional volume totalled $519 million for USD order book trades and €110 million for Euro order book trades indicating that USD order books are more popular than Euro order book. USD trades are also responsible for trading approximately 82,836 BTC daily while Euro trades account for only 17,260 BTC. This implies that either Bitcoin trading is more popular in the U.S. or that, of these two currency options, the USD is the preferred currency for Bitcoin transactions. The daily transactional volume for the sampled exchanges accounts for 81% and 74% of all trading activity in the USD and Euro Bitcoin markets, respectively. Therefore, this study encapsulated a significant proportion of the total Bitcoin market and the results reasonably characterise the total market.

Looking toward the size of the transactions the sample encompasses approximately 81.15% and 74.21% of the total trading volume, as measured in BTC, for USD and Euro markets, respectively. While the difference is minimal, it implies that the transactions executed in the sampled exchanges are larger than those that occur in out-of-sample exchanges. This is supported by the data on the total number of daily trades. Total daily trades are listed as 229,060 and 68,614 for USD and Euro markets, respectively. This encapsulates 78% of all USD trades and 83% of all Euro trades. In USD order books, the six sampled exchanges are responsible for 81% of all trading based on daily dollar transactional volume. Given that is only responsible for 78% of all transactions this data provides further support that the sampled USD/BTC order books or typically larger than those of the out-of-sample exchanges.

However, the opposite appears to be true to Euro/BTC order books. With 74% of the Euro volume and 83% of the total number of transactions, the four samples exchanges are responsible for a greater number of smaller transactions. In spite of these differences, the average trade sizes for USD and Euro order book trades are similar at $1,847 and €1,831 respectively. Accounting for exchange rates over the sample period makes the Euro trades slightly more valuable, on average, than USD trades.

Table 4-2 - Descriptive Statistics (Sample)

Panel A: USD ($)

	Mean	Std. Dev.	Q1	Q2	Q3
Sample - All					
Total Volume (USD) (millions)	519.18	627.65	148.93	299.80	644.16
Market Share (Sample - USD)	0.81	0.11	0.73	0.85	0.90
Total Volume (BTC) (thousands)	82.84	54.00	44.30	68.70	104.60
Market Share (Sample - BTC)	0.81	0.10	0.73	0.85	0.90
Total Trades Per Day (thousands)	229.06	167.17	117.10	180.54	278.48
Market Share (Sample - Trades Per Day)	0.78	0.13	0.72	0.83	0.87
Average Trade Size	1,847.29	1,203.33	1,095.57	1,767.84	2,498.39
Sample - First Half					
Total Volume (USD) (millions)	583.80	803.75	96.19	244.03	711.19
Market Share (Sample - USD)	0.81	0.11	0.72	0.86	0.90
Total Volume (BTC) (thousands)	97.39	59.21	59.37	83.26	121.34
Market Share (Sample - BTC)	0.81	0.11	0.73	0.86	0.90
Total Trades Per Day (thousands)	257.52	204.09	124.44	194.58	326.44
Market Share (Sample - Trades Per Day)	0.71	0.14	0.59	0.72	0.85
Average Trade Size	1,661.79	1,570.76	763.09	1,280.49	2,481.31
Sample - Second Half					
Total Volume (USD) (millions)	454.55	365.41	192.22	329.83	606.00
Market Share (Sample - USD)	0.81	0.10	0.74	0.84	0.89
Total Volume (BTC) (thousands)	68.28	43.62	37.55	56.30	86.35
Market Share (Sample - BTC)	0.81	0.10	0.74	0.84	0.89
Total Trades Per Day (thousands)	200.60	112.35	114.08	166.76	259.37
Market Share (Sample - Trades Per Day)	0.86	0.06	0.81	0.85	0.90
Average Trade Size	2,032.80	599.91	1,582.43	2,016.53	2,502.63

Table 4-2 - Descriptive Statistics (Sample) - continued

Panel B: Euro (€)

	Mean	Std. Dev.	Q1	Q2	Q3
Sample - All					
Total Volume (Euro) (millions)	110.42	634.49	30.86	56.56	100.66
Market Share (Sample - Euro)	0.74	0.18	0.71	0.80	0.85
Total Volume (BTC) (thousands)	17.26	10.69	9.92	14.65	20.58
Market Share (Sample - BTC)	0.74	0.17	0.71	0.80	0.85
Total Trades Per Day (thousands)	68.61	54.96	38.29	52.84	78.79
Market Share (Sample - Trades Per Day)	0.83	0.10	0.79	0.87	0.90
Average Trade Size	1,831.53	15,625.74	739.19	1,027.45	1,358.66
Sample - First Half					
Total Volume (Euro) (millions)	141.87	894.56	21.18	48.10	107.88
Market Share (Sample - Euro)	0.79	0.09	0.76	0.81	0.85
Total Volume (BTC) (thousands)	19.71	11.11	12.55	17.14	23.04
Market Share (Sample - BTC)	0.80	0.08	0.76	0.81	0.85
Total Trades Per Day (thousands)	78.77	70.46	35.93	57.62	92.83
Market Share (Sample - Trades Per Day)	0.85	0.06	0.82	0.87	0.89
Average Trade Size	2,376.60	22,079.71	590.87	845.77	1,152.16
Sample - Second Half					
Total Volume (Euro) (millions)	78.98	54.23	37.89	69.88	98.40
Market Share (Sample - Euro)	0.69	0.22	0.63	0.77	0.84
Total Volume (BTC) (thousands)	14.81	9.65	8.43	11.65	17.47
Market Share (Sample - BTC)	0.69	0.22	0.63	0.77	0.84
Total Trades Per Day (thousands)	58.45	29.50	38.83	50.13	68.15
Market Share (Sample - Trades Per Day)	0.81	0.12	0.71	0.87	0.91
Average Trade Size	1,286.47	468.98	872.46	1,284.11	1,567.79

Note. This table contains the means, standard deviations, and medians (Q2) as well as the first (Q1) and third (Q3) quartiles of various measure. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day. 'Sample – All' contains results over the entire sample period (1 January 2017 to 31 March 2019) while 'Sample – First Half' and 'Sample – Second Half uses data from 1 January 2017 to 14 February 2018 and 15 February 2018 to 31 March 2019, respectively. Volume (USD/Euro) is the total USD/Euro volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. Market Share (USD/Euro) is the proportion of USD/Euro volume captured by the sampled exchanges. Volume (BTC) is the total volume, measured in Bitcoin, (reported in thousands) of Bitcoin transactions and consists of data from both in and out-of-sample exchanges. Market Share (BTC) is the proportion of BTC volume captured by the sampled exchanges. Trades Per Day is the total number of BTC transactions (reported in thousands) and consists of both in and out-of-sample exchanges. Market Share (Trades Per Day) is the proportion of trades captured by the sampled exchanges. Average Trade Size (USD/Euro) is the average size of each transaction, measured in its respective currency (USD/Euro).

Table 4-2 also differentiates between the first and second half of the sample period. Total dollar transactional volume decreases from $584 million to $454 million. Over the same period the USD market share of transactions that the sample captures remain constant at 81% implying that the overall Bitcoin market when traded against the USD, is shrinking. This is to be expected as BTC peaked in price at $19,783 on December 17 2017. This period corresponds with the height of BTC's popularity in the media and precedes a period of significant devaluation.

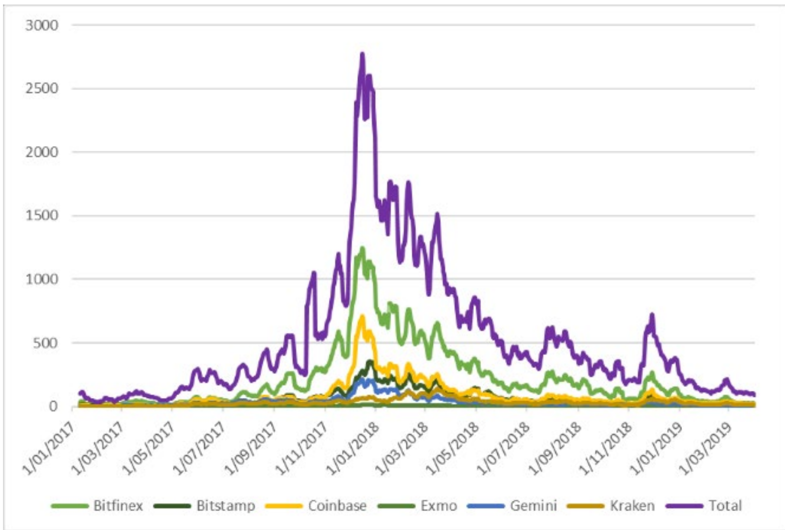
Figure 4-5 provides support for the conclusion regarding the size of the USD/BTC market. Panel A in Figure 4-5 shows a significant increase in the size of the USD/BTC market over the study period with a peak in daily trading volume of approximately $2.75 billion around the time of the peak BTC price. Trading volume decreased quickly after this period. Euro exchanges saw a decrease in daily transactional volume from €142 million to €79 million over the same period. Panel B in Figure 4-5 shows an increase in daily volume similar to that of the USD market. Daily Euro volume peaked at approximately €325 million, however, unlike the USD market, the Euro market is able to sustain the greater level of volume over a roughly three-month period before returning to a more sustainable level. The sample accounts for 79% of the trading volume in the first half of the study but decreases to 69% in the second half. This implies that while the Euro/BTC market shrank over the study period, the investors also looked for opportunities to trade in smaller competing exchanges. According to Figure 4-5 both the USD and Euro market saw a resurgence in activity around September 2018 and the 2018 Christmas season.

While markets shrunk with respect to volume, the average size of transactions increased from $1,662 to $2,032. However, the dollar market share remains constant over the period, and that the sample capture 71% of all trades in the first half of the sample and 85.5% in the second half. Therefore, while the remaining USD/BTC transactions were increasing in size for out-of-sample exchanges, the sample exchanges experience a reduction in transaction size. Once again, the Euro market behaves quite oppositely. Average Euro transaction sizes decrease over the sample period from €2,376 to €1,286, as do the market share of trades and volume that are captured by the sample, which decreased from 79% to 68% and €142 million to €79 million, respectively. This implies an overall decrease in the size of the Euro/BTC market over the trading period. Euro traders migrate to out-of-sample exchanges over the sample period while USD traders concentrate on the in-sample exchanges.

These findings are supported by Figure 4-6 which shows the market shares of all USD and Euro transactions that are captured by the sampled exchange. While USD results present some variations the overall sampled market share remains constant, as discussed previously. However, the results evidence significant variability in the Euro market over a five-month period at the start of 2019.

Over this period sampled Euro market share drops to a minimum of 19% but return to its previous levels shortly after. This five-month period in the Euro market represents a temporary phenomenon and, if removed from the study, would bring the Euro figures more in line with the USD figures in that a roughly constant market share of transaction volume captured by the sampled exchanges. Future research and further data collection are needed to derive the motivations behind investors' desire to migrate to a less dominant exchanges and why the change was not made permanent.

Panel A: USD ($)



Panel B: Euro (€)

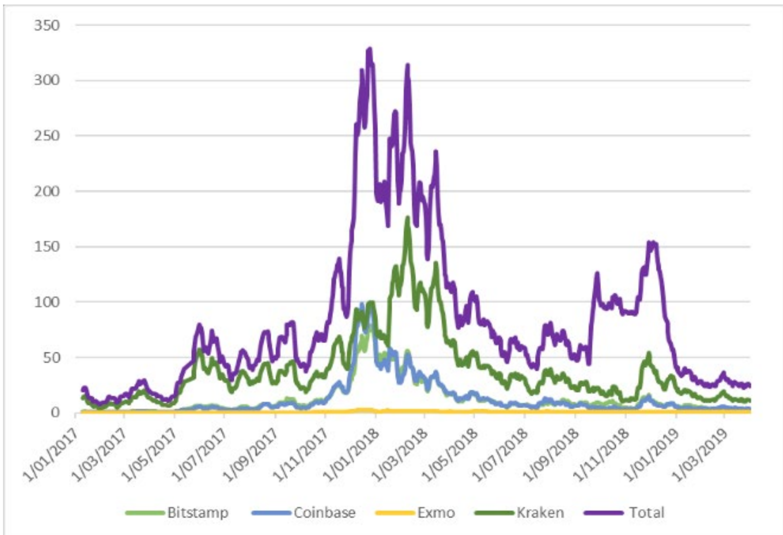


Figure 4-5 – Bitcoin Trading Volume (Exchange)

Note. This graph displays the total transactional volume of Bitcoin. Volume (USD/Euro) is the total USD/Euro volume (reported in millions) of Bitcoin (BTC) transaction. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Individual exchange data is displayed along with the total daily transactional volume which includes out-of-sample exchanges. The displayed results are based on a 10-day moving average.

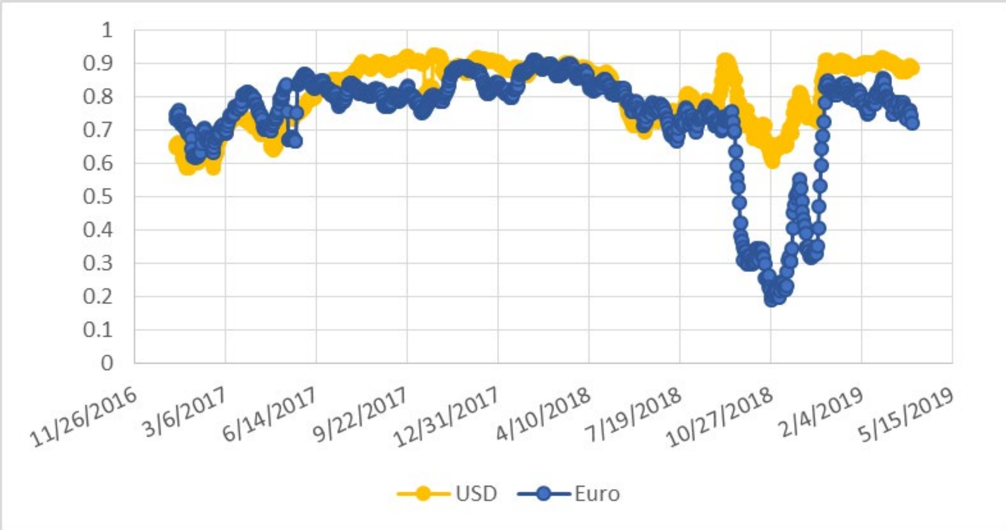


Figure 4-6 – Bitcoin Market Share (Sampled Exchanges)

Note. This figure presents the market share of total daily transactions that are captured by the sampled exchange. Market shares are presented separately for USD and Euro order books. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). The displayed results are based on a 10-day moving average.

Table 4-3 and Table 4-4 presents descriptive statistical data on the sampled exchanges. Data for all USD order books including Bitfinex, Bitstamp, Coinbase, Exmo, Gemini and Kraken are found in Table 4-3 while Table 4-4 contains Euro order book data for Bitstamp, Coinbase, Exmo and Kraken. Only two of the sampled exchanges, Bitfinex and Gemini, exclusively operate USD order books while the remaining exchanges operate in at least two currencies, with the Chinese Yuan being another popular medium of exchange.

Table 4-3: Descriptive Statistics (USD Exchanges)

	Panel A: Bitfinex					*Panel B: Bitstamp*				
	Mean	Std. Dev.	Q1	Q2	Q3	Mean	Std. Dev.	Q1	Q2	Q3
Volume (USD) (millions)	217.42	281.11	42.97	110.85	274.67	66.99	76.77	20.90	39.99	87.26
Market Share (USD)	0.37	0.09	0.29	0.37	0.44	0.14	0.03	0.11	0.13	0.16
Volume (BTC) (thousands)	32.59	25.97	14.45	25.22	44.20	11.25	7.76	5.94	9.49	14.51
Market Share (BTC)	0.37	0.09	0.29	0.37	0.44	0.14	0.03	0.11	0.13	0.16
Price (USD)	5,536.08	3,544.86	2,756.39	4,646.19	7,377.97	5,517.11	3,562.21	2,757.58	4,613.42	7,389.03
σ	5.69	7.55	1.49	3.20	6.13	5.49	7.21	1.47	3.14	6.03
BASp (x100)	0.02	0.02	0.00	0.01	0.03	0.09	0.05	0.05	0.09	0.12
Trades Per Day (thousands)	66.47	61.65	25.63	45.86	84.85	24.45	21.27	9.89	18.05	32.05
Market Share (Trades Per Day)	0.26	0.07	0.21	0.27	0.32	0.10	0.03	0.08	0.10	0.12
Average Trade Size	2,563.89	1,102.07	1,569.45	2,522.86	3,443.87	2,353.76	804.64	1,799.31	2,346.85	2,898.53

	Panel C: Coinbase					*Panel D: Exmo*				
	Mean	Std. Dev.	Q1	Q2	Q3	Mean	Std. Dev.	Q1	Q2	Q3
Volume (USD) (millions)	88.97	132.87	24.50	43.49	96.17	3.11	3.02	0.67	2.43	4.13
Market Share (USD)	0.16	0.04	0.13	0.16	0.19	0.01	0.01	0.00	0.01	0.01
Volume (BTC) (thousands)	13.55	10.74	6.73	10.49	16.94	0.45	0.21	0.24	0.49	0.58
Market Share (BTC)	0.16	0.04	0.13	0.16	0.19	0.01	0.01	0.00	0.01	0.01
Price (USD)	5,530.16	3,587.31	2,768.13	4,646.37	7,385.02	5,617.35	3,689.41	2,726.06	4,681.75	7,362.97
σ	5.22	7.29	1.29	2.90	5.70	5.51	7.13	1.94	3.33	5.96
BASp (x100)	0.01	0.03	0.00	0.00	0.02	0.29	0.09	0.24	0.28	0.34
Trades Per Day (thousands)	59.01	43.83	34.53	47.63	68.44	8.46	6.92	4.00	6.44	10.28
Market Share (Trades Per Day)	0.27	0.09	0.21	0.24	0.32	0.04	0.01	0.03	0.04	0.04
Average Trade Size	1,152.35	689.01	611.10	957.25	1,589.67	393.71	299.49	124.51	368.90	546.84

Note. This table contains the means, standard deviations, and medians (Q2) as well as the first (Q1) and third (Q3) quartiles of various measure for each USD cryptocurrency exchange. Panels A - F contain data for the following exchanges: Bitfinex, Bitstamp, Coinbase, Exmo, Gemini and Kraken. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Volume (USD) is the total USD volume (reported in millions) of Bitcoin (BTC) transactions for the exchange. Market Share (USD) is the proportion of USD volume captured by the exchange. Volume (BTC) is the total volume, measured in Bitcoin, (reported in thousands) of Bitcoin transactions for the exchange. Market Share (BTC) is the proportion of BTC volume captured by the exchange. Price (USD) is the average transaction price per BTC on the exchange. σ represents volatility and is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Trades Per Day is the total number of BTC transactions (reported in thousands) for the exchange. Market Share (Trades Per Day) is the proportion of trades captured by the exchange. Average Trade Size (USD) is the average size of each transaction in the exchange, measured in its respective currency (USD).

Table 4-3: Descriptive Statistics (USD Exchanges) – continued

	Panel E: Gemini					Panel F: Kraken				
	Mean	Std. Dev.	Q1	Q2	Q3	Mean	Std. Dev.	Q1	Q2	Q3
Volume (USD) (millions)	34.76	47.13	8.41	20.02	40.17	31.30	30.45	12.04	21.84	41.37
Market Share (USD)	0.07	0.04	0.05	0.06	0.08	0.07	0.03	0.05	0.07	0.09
Volume (BTC) (thousands)	5.95	5.25	2.43	4.55	7.86	5.57	3.97	2.96	4.50	7.10
Market Share (BTC)	0.07	0.04	0.05	0.06	0.08	0.07	0.03	0.05	0.07	0.09
Price (USD)	5,525.68	3,579.52	2,763.59	4,645.50	7,385.86	5,521.38	3,568.17	2,759.28	4,644.58	7,385.57
σ	5.27	7.28	1.24	2.96	5.86	5.44	7.17	1.45	3.13	6.08
BASp (x100)	0.03	0.04	0.01	0.02	0.04	0.09	0.09	0.03	0.06	0.13
Trades Per Day (thousands)	12.21	12.09	3.85	8.20	15.85	15.86	12.51	6.80	12.87	21.38
Market Share (Trades Per Day)	0.05	0.02	0.03	0.04	0.06	0.07	0.03	0.05	0.07	0.08
Average Trade Size	2,497.04	1,065.28	1,735.52	2,397.24	3,111.59	1,833.50	780.29	1,089.11	1,919.82	2,467.99

The most popular exchange for the USD traders is Bitfinex with an average daily transactional volume of $217 million which represents 36.8% of total USD/BTC volume, including out-of-sample exchanges. Coinbase and Bitstamp are the next more popular USD exchanges with $90 million and $67 million in total daily USD transactional volume, respectively. Coinbase and Bitstamp represent 16% and 13.5% of all USD/BTC market activity. With the exception of Exmo, Gemini and Kraken are the smallest of the sampled exchanges with approximately 6.8% and 7.1% of the total market share, respectively. Exmo is the smallest sampled USD/BTC exchange and accounts for only 0.7% of all USD transactions. Though a minor exchange, Exmo data is included in the study in order to test the robustness of the results with respect to the overall size/popularity of the exchange. Euro markets are noticeably more concentrated over the sample period. Kraken is the dominant exchange for EURO/BTC trading an encompasses 74% of all Euro/BTC trades. Bitstamp and Coinbase maintain similar average market shares of 12.1% and 11.4%, respectively, while Exmo trails with 1.3%. Figure 4-5 displays the exchange specific transactional volume data for both USD and Euro exchanges and shows that while the daily transactional volume fluctuates over time, each exchanges ranking within its respective currency market remains constant (Figure 4-7).

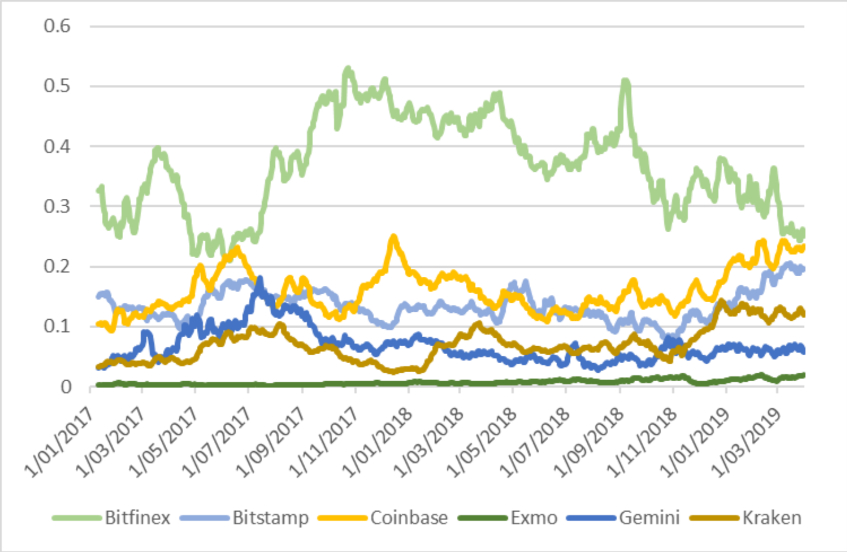
Table 4-4: Descriptive Statistics (Euro Exchanges)

	Panel A: Bitstamp					***Panel B: Coinbase***				
	Mean	Std. Dev.	Q1	Q2	Q3	Mean	Std. Dev.	Q1	Q2	Q3
Volume (Euro) (millions)	12.05	17.40	2.95	6.34	12.56	12.09	20.73	2.58	5.01	12.12
Market Share (Euro)	0.12	0.06	0.08	0.12	0.16	0.11	0.06	0.06	0.11	0.15
Volume (BTC) (thousands)	2.11	1.84	0.98	1.60	2.66	1.96	1.98	0.86	1.38	2.30
Market Share (BTC)	0.12	0.06	0.08	0.12	0.16	0.11	0.06	0.06	0.11	0.15
Price (Euro)	4,696.00	2,921.67	2,400.80	3,928.86	6,295.65	4,732.10	2,989.10	2,401.74	3,960.50	6,325.04
σ	4.82	6.20	1.48	2.87	5.19	4.36	6.41	1.07	2.48	4.76
BASp (x100)	0.23	0.11	0.14	0.21	0.30	0.04	0.05	0.01	0.02	0.06
Trades Per Day (thousands)	9.06	11.31	3.39	5.55	9.86	20.71	26.04	8.73	12.35	21.14
Market Share (Trades Per Day)	0.11	0.05	0.08	0.10	0.14	0.26	0.08	0.20	0.25	0.31
Average Trade Size	1,137.98	465.67	751.34	1,088.48	1,478.33	444.57	214.21	273.64	420.52	606.47

	Panel C: Exmo					***Panel D: Kraken***				
	Mean	Std. Dev.	Q1	Q2	Q3	Mean	Std. Dev.	Q1	Q2	Q3
Volume (Euro) (millions)	0.78	0.57	0.26	0.79	1.07	48.37	631.56	6.21	12.10	18.10
Market Share (Euro)	0.01	0.01	0.01	0.01	0.02	0.74	0.18	0.71	0.80	0.85
Volume (BTC) (thousands)	0.16	0.06	0.12	0.16	0.19	4.32	4.73	2.17	2.82	3.86
Market Share (BTC)	0.01	0.01	0.01	0.01	0.02	0.74	0.17	0.71	0.80	0.85
Price (Euro)	4,838.66	3,101.26	2,440.24	4,005.39	6,379.96	16.70	21.49	5.12	9.93	17.98
σ	5.33	6.16	2.14	3.51	5.71	1.07	0.97	0.39	1.05	1.65
BASp (x100)	0.68	0.38	0.50	0.59	0.72	0.00	0.00	0.00	0.00	0.00
Trades Per Day (thousands)	1.71	1.65	0.63	1.24	2.27	68.61	54.96	38.29	52.84	78.79
Market Share (Trades Per Day)	0.03	0.02	0.01	0.02	0.03	0.83	0.10	0.79	0.87	0.90
Average Trade Size	636.08	435.41	343.24	534.33	830.18	1,831.53	15,625.74	739.19	1,027.45	1,358.66

Note. This table contains the means, standard deviations, and medians (Q2) as well as the first (Q1) and third (Q3) quartiles of various measure for each Euro cryptocurrency exchange. Panels A - D contain data for the following exchanges: Bitstamp, Coinbase, Exmo, and Kraken. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Volume (Euro) is the total Euro volume (reported in millions) of Bitcoin (BTC) transactions for the exchange. Market Share (Euro) is the proportion of Euro volume captured by the exchange. Volume (BTC) is the total volume, measured in Bitcoin, (reported in thousands) of Bitcoin transactions for the exchange. Market Share (BTC) is the proportion of BTC volume captured by the exchange. Price (Euro) is the average transaction price per BTC on the exchange. σ represents volatility and is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Trades Per Day is the total number of BTC transactions (reported in thousands) for the exchange. Market Share (Trades Per Day) is the proportion of trades captured by the exchange. Average Trade Size (Euro) is the average size of each transaction in the exchange, measured in its respective currency (Euro).

Panel A: USD ($)



Panel B: Euro (€)

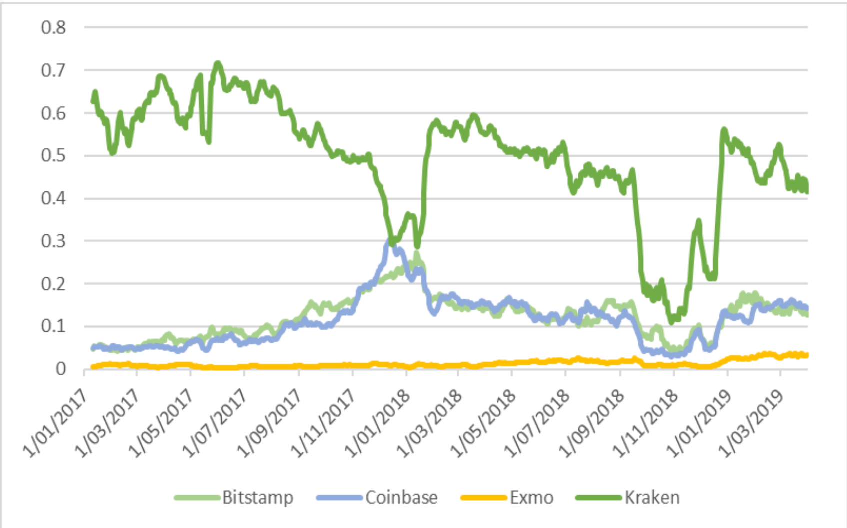


Figure 4-7 - Market Share (Exchange)

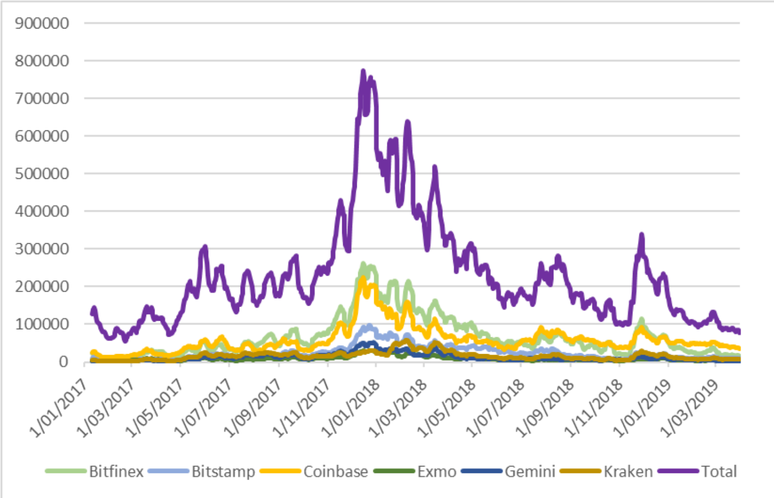
Note. This graph displays exchange market share data. Market Share (MS) is the exchange-specific market share, measured as a proportion of total volume. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Individual exchange data is displayed. Displayed results are based on a 10-day moving average.

In both Panels A and B of Figure 4-7, the dominant exchange maintains dominance over the sample period. Within the USD market the dominant exchange, Bitfinex, experiences some significant loss in market share during the middle of 2017 but begins to recover and reassert its dominance towards the end of July 2017. During this mid-2017 period, all non-dominant sampled exchanges attract additional liquidity and build market share. Figure 4-7 provides support for the notion that competing exchanges in the USD market can entice customers to migrate from the dominant exchange, Bitfinex, to their order books. This pattern repeats itself over the 2019 period where Bitfinex begins to lose market share while competing exchanges increase their market share of the trading volume. Towards March of 2019, the market shares for both Bitfinex and Coinbase converge indicating an increase in fragmentation as traders move away from a single dominant exchange.

A similar pattern is seen in the Euro market. While the dominant exchange, Kraken, maintains its dominance over the sample period, it does temporarily lose significant market share to Bitstamp and Coinbase around the end of 2017/start of 2018. However, as previously mentioned, Kraken loses significant market share toward the end of 2018. But traders preferred to move to out-of-sample exchanges during this period as indicated in Figure 4-7 where we see a decrease in market share for Kraken, while the market shares for Bitstamp and Coinbase remain fairly constant. In summary, the USD market is converging with competing exchanges able to attract liquidity way from the dominant exchange, Bitfinex, while the Kraken is able to sustain its dominance over the Euro market.

While Bitfinex and Kraken dominate their respective market in terms of daily trading volume, data on the number of daily transactions illustrates a more competitive landscape. In the USD market Coinbase is competing with Bitfinex regarding the number of daily transactions. On average, Bitfinex executes 25.9% daily transactions while Coinbase executes 27.2%. However, given that the average transaction size of $1,152 is significantly smaller for Coinbase when compared to $2,563 for Bitfinex, Bitfinex is able to maintain its position as the top USD/BTC exchange by volume (Table 4-3).

Panel A: USD ($)



Panel B: Euro (€)

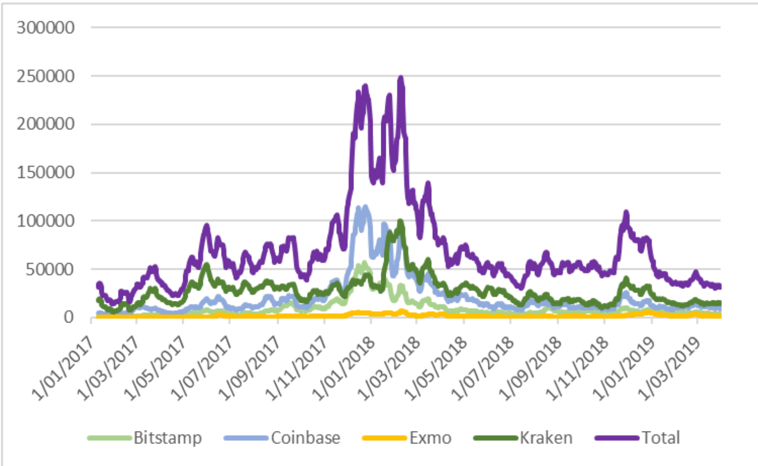
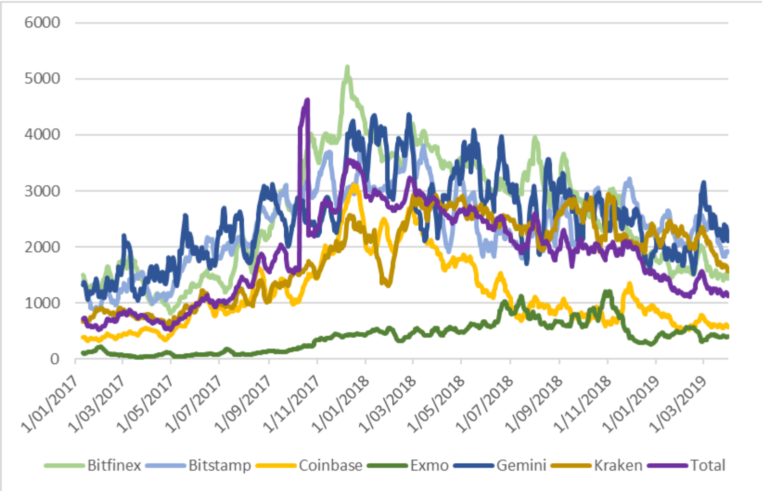


Figure 4-8 - Number of Daily Trades by Exchange

Note. This graph displays information on the number of daily Bitcoin (BTC) transactions. The total number of BTC transactions and consists of both in and out-of-sample exchanges. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Individual exchange data is displayed along with the total volume which includes out-of-sample exchanges. The displayed results are based on a 10-day moving average.

Once again, the analysis shows a more dominant relationship in the Euro market. Kraken dominates by daily transactional volume and is also able to transact 83% of all Euro/BTC trades over the sample period. The next best result comes from Coinbase who transact roughly 26.3% of all transactions, according to Table 4-4. However, while Coinbase executes the second largest number of transactions, it also executes the smallest transaction, on average, of €444. Even Exmo, who is only responsible for 2.5% of all trades, has an average trade size of €636. In the Euro market Bitstamp and Coinbase both attract roughly 12% of all Euro volume. However, Bitstamp attracts fewer larger transactions while Coinbase is responsible for executing a greater number of smaller transactions. These results are further supported by Figure 4-9.

Panel A: USD ($)



Panel B: Euro (€)

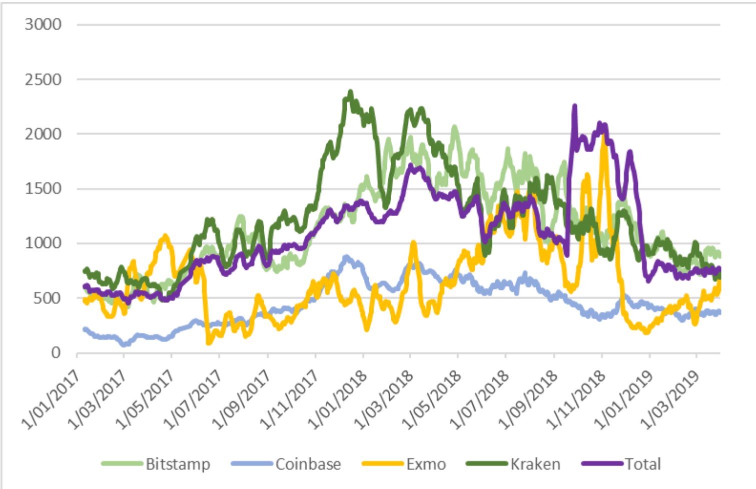


Figure 4-9 - Average Trade Size by Exchange

Note. This graph displays information on the average sizes of transactions. Average Trade Size (USD/Euro) is the average size of each transaction, measured in its respective currency (USD/Euro). Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Individual exchange data is displayed along with the total market which includes out-of-sample exchanges. The displayed results are based on a 10-day moving average.

Table 4-5 and Table 4-6 report results regarding the correlations amongst the independent variables in the study for USD and Euro markets, respectively. When looking at the key fragmentation measures, Frag and Frag (Others), it is evident that the exchanges in the study have a significant impact on the microstructure of the Bitcoin market within their respective currency's order book. Correlation coefficients closer to zero identify order books that are less dominant by a single exchange. Table 4-5 Panel A reports a correlation coefficient of 0.68 while Table 4-6 Panel A reports a result of 0.59. The exchange specific correlation coefficients report that the USD and Euro order books are dominated by the Bitfinex and Kraken respectively. Correlation coefficients of -0.02 for Bitfinex and -0.05 for Kraken indicate that the overall market microstructure relies heavily on this inclusion of these exchanges within their order books. Other exchanges, if removed from the fragmentation measure, have a negligible impact on the structure of the market as indicated by their near-perfect positive correlations between Frag and Frag (Others). This is further supported by the correlation coefficients between Frag and the remaining independent variables. Table 4-5 Panel B and Table 4-6 Panel D, representing the dominant USD and Euro exchanges of Bitfinex and Kraken, respectively, display larger variations between coefficients for the two Frag measures. Less influential markets displayed in the remaining panels report only minimal differences. Additional findings pertaining to the correlation coefficients are discussed in the regression results below.

Table 4-5: Correlations (USD Exchanges)

Panel A: All

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.68	1					
(3)	MS (USD)	-0.11	0.62	1				
(4)	σ	-0.68	-0.45	0.08	1			
(5)	BASp	0.05	-0.19	-0.46	0.02	1		
(6)	Vol	-0.67	-0.46	0.07	0.95	-0.07	1	
(7)	AvgTS	-0.26	0.05	0.45	0.34	-0.38	0.39	1

Panel B: Bitfinex

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	-0.02	1					
(3)	MS (USD)	-0.91	0.40	1				
(4)	σ	-0.69	0.01	0.65	1			
(5)	BASp	0.01	-0.13	-0.08	-0.02	1		
(6)	Vol	-0.67	0.05	0.65	0.97	-0.11	1	
(7)	AvgTS	-0.69	0.31	0.76	0.79	-0.35	0.84	1

Table 4-5: Correlations (USD Exchanges) - continued

Panel C: Bitstamp

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.99	1					
(3)	MS (USD)	0.03	0.18	1				
(4)	σ	-0.69	-0.69	-0.05	1			
(5)	BASp	-0.15	-0.15	0.01	0.28	1		
(6)	Vol	-0.67	-0.68	-0.11	0.96	0.15	1	
(7)	AvgTS	-0.59	-0.56	0.13	0.76	-0.07	0.80	1

Panel D: Coinbase

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.97	1					
(3)	MS (USD)	-0.13	0.10	1				
(4)	σ	-0.69	-0.66	0.17	1			
(5)	BASp	0.21	0.23	0.06	-0.22	1		
(6)	Vol	-0.67	-0.65	0.12	0.96	-0.33	1	
(7)	AvgTS	-0.67	-0.62	0.21	0.89	-0.29	0.92	1

Panel E: Gemini

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.99	1					
(3)	MS (USD)	0.09	0.19	1				
(4)	σ	-0.67	-0.66	-0.02	1			
(5)	BASp	0.09	0.05	-0.43	0.10	1		
(6)	Vol	-0.67	-0.67	-0.03	0.93	0.06	1	
(7)	AvgTS	-0.36	-0.34	0.23	0.57	-0.04	0.65	1

Panel F: Exmo

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	1.00	1					
(3)	MS (USD)	0.15	0.15	1				
(4)	σ	-0.67	-0.67	-0.07	1			
(5)	BASp	0.17	0.17	-0.45	-0.22	1		
(6)	Vol	-0.67	-0.67	-0.20	0.96	-0.28	1	
(7)	AvgTS	-0.21	-0.21	0.66	0.46	-0.58	0.41	1

Panel G: Kraken

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.99	1					
(3)	MS (USD)	0.05	0.13	1				
(4)	σ	-0.66	-0.66	-0.14	1			
(5)	BASp	0.06	0.02	-0.47	0.01	1		
(6)	Vol	-0.67	-0.68	-0.12	0.93	-0.14	1	
(7)	AvgTS	-0.37	-0.35	0.30	0.46	-0.67	0.58	1

Note. This table contains the correlation coefficients between various measure for each USD exchange in the sample. Panel A contains correlation measures based on all USD exchanges while the remaining figures in Panels B - G contain exchange specific data. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Frag is the result of calculating 1 minus the Herfindahl-Hirschman using exchange volume data. Frag (Other) is similar to Frag except it excludes market share data for the current exchange. MS is the exchange-specific market share, measured as a proportion of total volume. σ is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Vol is the total USD volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. AvgTS is the average size of each transaction in the exchange, measured in its respective currency (USD).

Table 4-6: Correlations (Euro Exchanges)

Panel A: All

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.59	1					
(3)	MS (Euro)	-0.18	0.66	1				
(4)	σ	-0.02	-0.05	0.01	1			
(5)	BASp	-0.24	-0.38	-0.36	0.12	1		
(6)	Vol	0.18	0.11	0.01	0.84	-0.07	1	
(7)	AvgTS	0.15	0.41	0.44	0.39	-0.02	0.36	1

Panel B: Bitstamp

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.99	1					
(3)	MS (Euro)	-0.02	0.10	1				
(4)	σ	0.00	0.08	0.67	1			
(5)	BASp	-0.52	-0.53	-0.23	-0.07	1		
(6)	Vol	0.18	0.24	0.48	0.86	-0.17	1	
(7)	AvgTS	0.17	0.23	0.57	0.71	-0.47	0.70	1

Panel C: Coinbase

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	0.99	1					
(3)	MS (Euro)	-0.01	0.13	1				
(4)	σ	-0.08	0.02	0.69	1			
(5)	BASp	-0.56	-0.57	-0.27	-0.13	1		
(6)	Vol	0.18	0.26	0.49	0.84	-0.26	1	
(7)	AvgTS	0.21	0.30	0.72	0.79	-0.51	0.73	1

Panel D: Exmo

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	1.00	1					
(3)	MS (Euro)	0.32	0.33	1				
(4)	σ	0.06	0.06	-0.18	1			
(5)	BASp	-0.53	-0.53	-0.46	0.02	1		
(6)	Vol	0.18	0.18	-0.36	0.85	-0.09	1	
(7)	AvgTS	0.33	0.33	0.26	-0.11	-0.02	-0.08	1

Panel E: Kraken

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	Frag	1						
(2)	Frag (Others)	-0.05	1					
(3)	MS (Euro)	-0.96	0.21	1				
(4)	σ	-0.04	-0.68	-0.07	1			
(5)	BASp	-0.50	-0.13	0.41	0.18	1		
(6)	Vol	0.18	-0.51	-0.32	0.85	0.04	1	
(7)	AvgTS	0.01	-0.63	-0.11	0.85	0.01	0.79	1

Note. This table contains the correlation coefficients between various measure for each USD exchange in the sample. Panel A contains correlation measures based on all Euro exchanges while the remaining figures in Panels B - E contain exchange specific data. Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Frag is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1. Frag (Other) is similar to Frag except it excludes market share data for the current exchange. MS is the exchange-specific market share, measured as a proportion of total volume. σ is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Vol is the total Euro volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. AvgTS is the average size of each transaction in the exchange, measured in its respective currency (Euro).

Figure 4-10 groups all the correlation coefficients in the study. It ignores any correlations between *Frag* and *Frag (Others)* as the measures are constructed in a similar fashion and often result in (nearly) perfect positive correlations. Note that the majority of variable pairs are not highly correlated with each other. However, there is a subset of variables with higher correlations. This result was noted previously in the multicollinearity checks contained in Section 4.6.4.4.

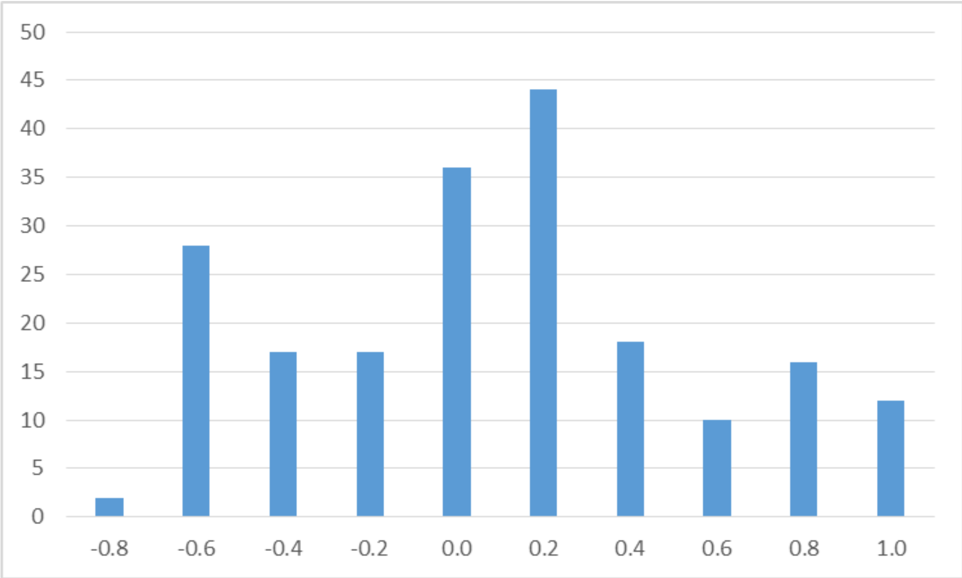


Figure 4-10 - Correlation Coefficient Distribution

Note. This figure contains a histogram of correlation coefficients found in Table 4-5 and Table 4-6. Correlation coefficients are grouped into categories that are 0.2 wide. The x-axis label indicates the maximum allowable value for each category. Note that correlations = 1 where parameters are compared against themselves are removed from this figure.

4.7.2 Fragmentation and Price Discovery

This section reports on the results of the fragmentation and price discovery measures that form the basis for this chapter. Panel A in Table 4-6 indicates that the microstructure of the USD Bitcoin market has remained consistent over the study period. Frag is reported as 0.8 across the entire sample period while the first and second half Frag measures are reported to be 0.79 and 0.8, respectively. This is evidence that the overall level of competition is constant across the sample period and that no major fragmenting events occurred caused by one exchange growing in popularity relative to its competitors. This is further supported by the Market Share (MS) measures in Table 4-6 Panel A which also remain stable at 0.13 and 0.14.

However, the Euro Bitcoin markets, whose fragmentation measures are presented in Panel B of Table 4-6, show that microstructure of the market is not constant over the sample period. Fragmentation (*Frag*) across the sample period is reported to be 0.7 while the same measure is reported to be 0.64 and 0.76 over the first and second half of the sample period, respectively.

The increase in Frag over time is representative of an increase in fragmentation throughout the sample period. The *MS* further supports this finding results in Table 4-7 Panel B which show that, on average, each exchange captures 18% of the total transactional volume while first and second half measures again support an increase in fragmentation with *MS* results of 0.2 and 0.17, respectively. This is further proof that transactional volume moved away from the dominant exchange, Kraken. Over time, European investors begin to favour satellite exchanges and the market becomes less centralised around a single dominant exchange.

Table 4-7: Market Fragmentation Measures

Panel A: USD ($)

	Mean	Std. Dev.	Q1	Q2	Q3
1-HHI					
Sample - All	0.797	0.063	0.748	0.806	0.843
Sample - First Half	0.795	0.071	0.733	0.806	0.850
Sample - Second Half	0.800	0.053	0.765	0.806	0.833
Market Share (USD)					
Sample - All	0.135	0.125	0.046	0.107	0.172
Sample - First Half	0.135	0.127	0.044	0.109	0.171
Sample - Second Half	0.135	0.123	0.048	0.106	0.173

Panel B: Euro (€)

	Mean	Std. Dev.	Q1	Q2	Q3
1-HHI					
Sample - All	0.701	0.122	0.624	0.693	0.756
Sample - First Half	0.639	0.093	0.566	0.642	0.711
Sample - Second Half	0.763	0.116	0.682	0.733	0.828
Market Share (Euro)					
Sample - All	0.185	0.202	0.031	0.115	0.226
Sample - First Half	0.198	0.226	0.017	0.090	0.297
Sample - Second Half	0.172	0.173	0.034	0.126	0.179

Note. This table reports the means, standard deviations, and medians (Q2) as well as the first (Q1) and third (Q3) quartiles of the fragmentation measures used in the study. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated using all transactions in a single currency over a single trading day. 'Sample – All' contains results over the entire sample period (1 January 2017 to 31 March 2019) while 'Sample – First Half' and 'Sample –

Second Half uses data from 1 January 2017 to 14 February 2018 and 15 February 2018 to 31 March 2019, respectively. Frag is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1. All exchanges reference the same 'Frag' figure for a given transaction day. MS is the exchange-specific market share, measured as a proportion of total volume.

The consistency in the USD Bitcoin market can partly be explained by the fact that there is no single dominant USD exchange. Table 4-3, Panel A reports Bitfinex as being the dominant USD Bitcoin exchange with a market share of 37% while Table 4-4 Panel D reports Kraken as the dominant Euro exchange with an average market share of 74%. As a result, there is more room for the evolution of the Euro market where competing exchanges can attract investors from the dominant exchange. Competition amongst USD exchanges is more realised upon the opening dates in the sample periods. This is further supported by the *Frag* measures in Table 4-7 which indicate more competition amongst USD exchanges compared to Euro exchanges, as indicated by the higher *Frag* value.

Upon initial analysis the information shares (IS) results contained in support the previous notion that the USD Bitcoin market is less centralised than the Euro Bitcoin market. Table 4-8, Panel A reports that on average USD exchanges individually contain 17% of all price adjusting information while Panel B reports that individual Euro exchanges contribute 25% of all price adjusting information. This is further supported by the individual exchange IS measures. Three of the six USD exchanges contain informational content in the double figures, ranging from 0.15 to 0.52. Bitfinex is a US-based exchange and is the leading informational source of US/BTC price information. The majority of price adjusting information in the Euro Bitcoin market, however, originates from the Kraken exchange which boasts an IS of 0.85. Kraken, which is headquartered in Europe, is also the only Euro exchange whose informational content reaches double figures. The remaining exchange, Bitstamp, Coinbase and Exmo represent only 7%, 6%, and 2% of the informational content, respectively, in the Euro Bitcoin market.

This provides support for H4-1 and indicated that no single exchange is responsible for advertising all price-relevant information. It also provides support for H4-4 in that the leading source of price adjusting information for a particular fiat currency/BTC pair are exchanges that are headquartered in the country where that fiat currency originates.

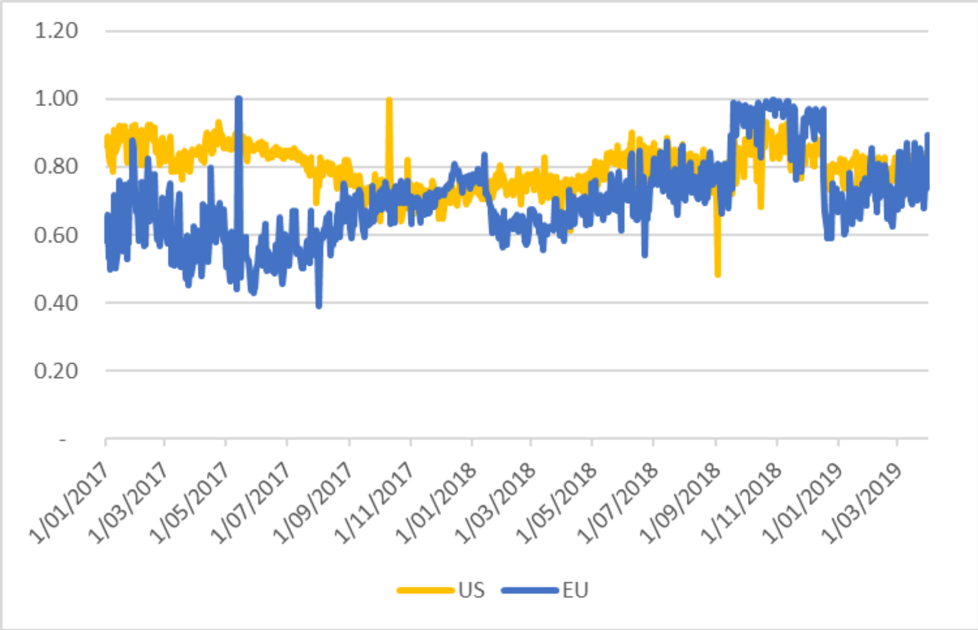


Figure 4-11 – Intra-Market Fragmentation (Bitcoin)

Note. This graph displays the fragmentation levels of both USD and Euro markets. Fragmentation (Frag) is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1Results are calculated using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019).

Figure 4-11 provides a visual representation of the change in market microstructure across USD and Euro order books. While both USD and Euro markets show inter-day variability in the level of fragmentation within their respective order books, the USD market shows greater consistency in the level of fragmentation while the overall upward trend in the Euro market measure of fragmentation indicated greater fragmentation over time as Kraken loses some of its dominance over the sample period.

Table 4-8: Information Share

Panel A: USD ($)

	Mean	Std. Dev.	Q1	Q2	Q3
All	0.167	0.178	0.034	0.080	0.233
Bitfinex	0.518	0.058	0.486	0.523	0.558
Bitstamp	0.153	0.030	0.133	0.150	0.171
Coinbase	0.236	0.041	0.211	0.233	0.257
Exmo	0.011	0.002	0.010	0.011	0.013
Gemini	0.039	0.009	0.034	0.038	0.044
Kraken	0.041	0.010	0.035	0.041	0.047

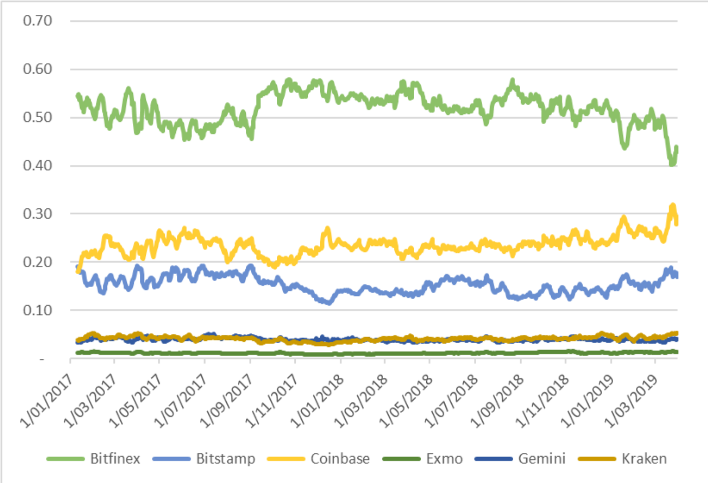
Panel B: Euro (€)

	Mean	Std. Dev.	Q1	Q2	Q3
All	0.250	0.349	0.034	0.061	0.367
Bitstamp	0.068	0.027	0.052	0.063	0.077
Coinbase	0.061	0.021	0.047	0.058	0.070
Exmo	0.021	0.008	0.015	0.018	0.023
Kraken	0.851	0.050	0.833	0.861	0.880

Note. This table reports values for Hasbrouck's (1995) information share (IS) for each exchange (Bitfinex, Bitstamp, Coinbase, Exmo, Gemini and Kraken). It reports means, standard deviations, and medians (Q2) as well as the first (Q1) and third (Q3) quartile value. Results are calculated for each exchange over a single trading day over the sample period (1 January 2017 to 31 March 2019). Panels A and B contain IS data based on order books and transactions conducted in USD ($) and Euro (€), respectively. All consists of data from each exchange operating under its respective currency.

Figure 4-12 provides further support for the centralisation of information in the Euro Bitcoin market. USD IS data contained in Panel A shows a greater dispersion of price adjusting information while Panel B shows that this information is more concentrated around a single exchange, Kraken.

Panel A: USD ($)



Panel B: Euro (€)

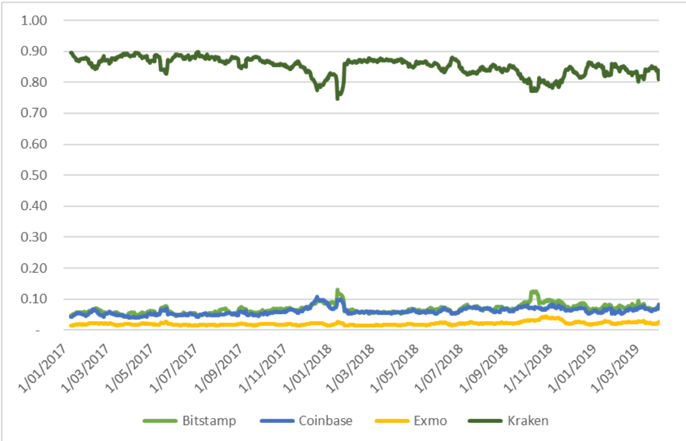


Figure 4-12 - Information Share by Exchange

Note. This graph displays the values for Hasbrouck's (1995) information share (IS) for each exchange (Bitfinex, Bitstamp, Coinbase, Exmo, Gemini and Kraken). Results are calculated for each exchange over a single trading day over the sample period (1 January 2017 to 31 March 2019). Panels A and B contain IS data based on order books and transactions conducted in USD ($) and Euro (€), respectively. The displayed results are based on a 10-day moving average.

4.7.3 Regression Results

This section reports on the results of the regression analysis conducted in this study. Regression results are found in Table 4-9 to Table 4-11 with Panels A and B containing results for USD and Euro order books, respectively. Beginning with the market share (MS) measure, the results support H4-2 in that increased market share for an exchange is positively related with an increase in the informational contents of the respective exchange's trades. Coefficients range from 0.05 to 0.685 in Panels A and B of Table 4-9.

Table 4-9: Regression Results (No Fixed Effects)

Panel A: USD ($)

	Bitfinex	Bitstamp	Coinbase	Exmo	Gemini	Kraken
Constant	-0.158	-0.027	-0.155	-0.007	0.112	0.136
	(-1.15)	(-0.41)	(-1.7) *	(-1.06)	(7.06) ***	(7.52) ***
Frag	0.445	0.115	0.178	0.009	0.051	0.047
	(6.43) ***	(6.31) ***	(6.41) ***	(5.98) ***	(7.66) ***	(7.6) ***
MS	0.610	0.372	0.460	0.205	0.050	0.059
	(11.86) ***	(13.35) ***	(14.5) ***	(6.99) ***	(5.12) ***	(5.36) ***
σ	-0.004	-0.005	-0.005	-0.001	0.008	0.007
	(-0.66)	(-1.37)	(-1.09)	(-1.96) **	(10.67) ***	(8.47) ***
BASp	0.006	0.015	-0.001	0.002	-0.001	0.000
	(3.19) ***	(8.3) ***	(-1.57)	(4.41) ***	(-3.67) ***	(-0.38)
Vol	0.002	-0.001	0.015	0.000	-0.007	-0.008
	(0.29)	(-0.22)	(2.73) ***	(0.75)	(-9.06) ***	(-9.18) ***
AvgTS	0.008	0.004	-0.016	0.000	0.003	0.002
	(0.81)	(0.91)	(-2.76) ***	(0.31)	(3.45) ***	(1.99) **
Fixed Effects	None	None	None	None	None	None
Adjusted R^2	0.340	0.364	0.236	0.327	0.244	0.272
N	820	820	820	820	820	820

Table 4-9: Regression Results (No Fixed Effects) - continued

Panel B: Euro (€)

	Bitstamp	Coinbase	Exmo	Kraken
Constant	-0.164	-0.038	-0.105	-0.325
	(-2.52) **	(-0.68)	(-1.56)	(-1.92) *
Frag	0.176	0.092	0.168	0.495
	(12.92) ***	(6.67) ***	(12.02) ***	(5.68) ***
MS	0.356	0.314	0.552	0.685
	(10.04) ***	(9.61) ***	(2.66) ***	(9.35) ***
σ	-0.016	-0.003	-0.011	0.006
	(-4.42) ***	(-0.82)	(-3.55) ***	(1.18)
BASp	0.026	0.008	0.021	0.013
	(5.84) ***	(5.56) ***	(4.27) ***	(3.73) ***
Vol	0.005	0.009	0.004	0.003
	(1.63)	(2.87) ***	(1.19)	(0.5)
AvgTS	0.011	-0.001	0.001	-0.007
	(2.01) **	(-0.22)	(0.65)	(-0.75)
Fixed Effects	None	None	None	None
Adjusted R^2	0.255	0.255	0.239	0.411
N	820	820	820	820

Note. This table contains the results of the panel regression analysis with no fixed effects. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated for each exchange using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Frag is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1. MS is the exchange-specific market share, measured as a proportion of total volume. σ is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Vol is the total USD/Euro volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. AvgTS is the average size of each transaction in the exchange, measured in its respective currency (USD/Euro). σ, BASp, Vol and AvgTS have been transformed using the natural logarithm (ln). T-statistics can be found in parentheses below each regression coefficient. *,** and *** identify results of 90%, 95%, and 99% statistical significance, respectively. Information on the relevant fixed effects, adjusted R^2 and number of observations are also reported.

The results are also robust for time fixed effects as shown in Panels A and B of Table 4-10, where coefficients range from 0.081 to 0.619. The results with time fixed effects in Table 4-10 are significant at the 1% level across all exchanges in both the USD and Euro markets, except for the Exmo Euro exchange. USD markets show greater consistency in the reported MS coefficients. More dominant USD exchanges with a greater market share of the transactional volume, such as Bitfinex and Bitstamp, are more likely to attract informed trades than less dominant exchanges. These results can be supported by the works of (Chowdhry & Nanda, 1991) who find that informed traders find greater difficulty participating in exchanges with less transactional volume.

These results are consistent with those in Chapter 3 where informed investors transacting in a dark pool experience a lower probability of execution and must return to the displayed order book to locate a counterparty to the transaction in a timely fashion. Informed investors are more likely to transact on the same side of the order book and therefore require a greater pool of uninformed traders with whom they can trade. Exchanges with lower levels of trading volume will have lower levels of uninformed trading activity. This results in less informational content to their trades as informed investors migrate to more liquid exchanges where the risk of finding a counterparty to the transaction is reduced. However, some informed trading will always follow the uninformed investors. Therefore, the results support hypothesis H4-2 and are consistent with the notion that greater market share is positively correlated with greater informational content in trades as there are more uninformed traders with whom the informed can transact. The results are also consistent with the idea that the informational content of transactions on more liquid exchange, that is those who capture a greater market share of transaction, is more sensitive to increases in market share. Increased sensitivity occurs as their large pool of uninformed investors is more likely to attract additional informed trade given the already greater probability of execution on these exchanges.

Overall market microstructure, as measured by Frag, has a positive relationship with the informational content of an exchange's transactions. This result is indicated by the positive regression coefficients for Frag across all sampled exchanges in both USD and Euro Bitcoin markets. Regression coefficients range from 0.01 to 0.495 in Table 4-9 and Table 4-10 and are consistently significant at the 1% level. These findings support hypothesis H4-3 in that the increased fragmentation of order books is positively related to increases in the informational content of an exchange's trades. The results can be explained by the theory presented by Mendelson (1987) who propose that smaller exchanges have difficulty in attracting informed activity without a sufficient pool of uninformed trades with which the informed can interact. Therefore, greater fragmentation leads to the migration of uninformed traders to the new exchanges. While some informed activity can follow the uninformed to the new exchanges, once again the level of uninformed activity is not enough to support these trades. The lack of support is due to an insufficient number of counterparties to the informed trades at the desired price level. This is consistent with the previous findings for MS which report that while increased market share does lead to more informed activity on an exchange, the increase in informational content in lower for less liquid exchanges due to their lower levels of uninformed trading compared to more dominant exchanges.

The lower *Frag* coefficients for less liquid exchanges such as Exmo also supports the notion that these exchanges find it more difficult to locate a counterparty for the informed traders when compared to more liquid exchanges (Mendelson, 1987). So when markets fragment and smaller exchanges entice some investors to transact in their order books, the increases in fragmentation they cause can support some level of informed trading activity, though not as must as more liquid exchanges. But once again, these smaller exchanges largely attract uninformed traders.

Table 4-10: Regression Results (Time Fixed Effects)

Panel A: USD ($)

	Bitfinex	Bitstamp	Coinbase	Exmo	Gemini	Kraken
Constant	-0.237	-0.079	-0.151	-0.002	0.133	0.148
	(-1.32)	(-1.08)	(-1.54)	(-0.29)	(7.44) ***	(7.59) ***
Frag	0.439	0.132	0.180	0.011	0.050	0.045
	(4.31) ***	(6.08) ***	(5.43) ***	(5.59) ***	(6.57) ***	(6.04) ***
MS	0.619	0.399	0.430	0.185	0.081	0.083
	(9.2) ***	(11.34) ***	(8.64) ***	(5.59) ***	(6.04) ***	(5.42) ***
σ	-0.009	-0.011	-0.009	0.000	0.008	0.007
	(-1.23)	(-2.66) ***	(-1.81) *	(-1.15)	(10.88) ***	(7.4) ***
BASp	0.019	0.023	0.005	0.002	-0.002	-0.001
	(3.39) ***	(6.83) ***	(3.09) ***	(4.06) ***	(-4.35) ***	(-0.52)
Vol	-0.002	0.000	0.010	0.000	-0.008	-0.008
	(-0.25)	(0.004)	(1.708) *	(-0.045)	(-9.38) ***	(-8.882) ***
AvgTS	0.025	0.003	-0.005	0.000	0.002	0.001
	(2.21) **	(0.58)	(-0.64)	(-1.45)	(2.44) **	(1.01)
Fixed Effects	Time	Time	Time	Time	Time	Time
Adjusted R^2	0.347	0.382	0.249	0.334	0.265	0.277
N	820	820	820	820	820	820

Table 4-10: Regression Results (Time Fixed Effects) - continued

Panel B: Euro (€)

	Bitstamp	Coinbase	Exmo	Kraken
Constant	-0.159	-0.002	0.001	-0.145
	(-2.2) **	(-0.04)	(0.02)	(-0.79)
Frag	0.161	0.093	0.140	0.404
	(8.47) ***	(4.85) ***	(7.74) ***	(4.22) ***
MS	0.347	0.342	0.012	0.604
	(7.58) ***	(7.54) ***	(0.04)	(7.72) ***
σ	-0.017	0.000	0.002	0.010
	(-3.46) ***	(-0.05)	(0.44)	(1.34)
BASp	0.032	0.008	0.019	0.010
	(4.88) ***	(4.31) ***	(3.31) ***	(1.28)
Vol	0.004	0.005	-0.003	-0.001
	(1.02)	(1.617)	(-0.91)	(-0.159)
AvgTS	0.011	0.002	0.007	-0.006
	(1.71) *	(0.3)	(2.72) ***	(-0.61)
Fixed Effects	Time	Time	Time	Time
Adjusted R^2	0.255	0.260	0.286	0.418
N	820	820	820	820

Note. This table contains the results of the panel regression analysis with time fixed effects. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated for each exchange using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). Frag is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1. MS is the exchange-specific market share, measured as a proportion of total volume. σ is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Vol is the total USD/Euro volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. AvgTS is the average size of each transaction in the exchange, measured in its respective currency (USD/Euro). σ, BASp, Vol and AvgTS have been transformed using the natural logarithm (ln). T-statistics can be found in parentheses below each regression coefficient. *,** and *** identify results of 90%, 95%, and 99% statistical significance, respectively. Information on the relevant fixed effects, adjusted R^2 and number of observations are also reported.

Since these less liquid order books attract more uninformed traders and informed ones from other displayed order book, the concentration of informed to uninformed investors increases in the dominant exchange, supporting both H4-2 and H4-3. This dilution in informed trading means that major exchanges like Bitfinex in the U.S. and Kraken in Europe lose more uninformed than informed order flow. As a result of the increased concentration of informed traders, the informational content of trading activity in the dominant exchange increases by a greater amount than their less liquid competitors. This, again, supports the findings in this study which reports consistently higher Frag regression coefficients for exchanges with higher market shares than those with smaller market shares. Even with a loss in market share, more liquid exchanges are still able to support larger degrees of informed trading due to their significant uninformed trading pool.

However, the increase in the informational content of exchanges resulting from increased fragmentation does not come without a cost. Greater informed trading on an exchange is consistent with greater levels of information asymmetry (Chowdhry & Nanda, 1991; Madhavan, 1995).

Table 4-11: Regression Results (Time Fixed Effects & Frag (Other))

Panel A: USD ($)

	Bitfinex	Bitstamp	Coinbase	Exmo	Gemini	Kraken
Constant	-0.284	-0.074	-0.139	-0.002	0.133	0.148
	(-1.6)	(-1.02)	(-1.43)	(-0.28)	(7.44) ***	(7.61) ***
Frag (Other)	0.608	0.132	0.179	0.011	0.050	0.045
	(4.76) ***	(6.13) ***	(5.43) ***	(5.59) ***	(6.52) ***	(6.07) ***
MS	0.279	0.362	0.367	0.184	0.071	0.076
	(7.93) ***	(9.87) ***	(6.94) ***	(5.58) ***	(5.13) ***	(4.97) ***
σ	-0.003	-0.010	-0.009	0.000	0.008	0.007
	(-0.41)	(-2.61) ***	(-1.76) *	(-1.14)	(10.87) ***	(7.41) ***
BASp	0.018	0.023	0.005	0.002	-0.002	-0.001
	(3.22) ***	(6.82) ***	(3.07) ***	(4.06) ***	(-4.37) ***	(-0.55)
Vol	-0.004	0.000	0.010	0.000	-0.008	-0.008
	(-0.55)	(-0.036)	(1.635)	(-0.047)	(-9.354) ***	(-8.89) ***
AvgTS	0.024	0.003	-0.004	0.000	0.002	0.001
	(2.09) **	(0.6)	(-0.58)	(-1.44)	(2.49) **	(1.03)
Fixed Effects	Time	Time	Time	Time	Time	Time
Adjusted R^2	0.351	0.382	0.249	0.334	0.265	0.277
N	820	820	820	820	820	820

Table 4-11: Regression Results (Time Fixed Effects & Frag (Other)) - continued

Panel B: Euro (€)

	Bitstamp	Coinbase	Exmo	Kraken
Constant	-0.151	0.003	0.002	-0.093
	(-2.1) **	(0.05)	(0.03)	(-0.58)
Frag (Other)	0.160	0.095	0.140	0.616
	(8.57) ***	(5.06) ***	(7.74) ***	(4.82) ***
MS	0.295	0.307	0.005	0.238
	(6.36) ***	(6.53) ***	(0.02)	(8.87) ***
σ	-0.017	0.000	0.002	0.021
	(-3.38) ***	(0.05)	(0.44)	(2.79) ***
BASp	0.032	0.008	0.019	0.011
	(4.82) ***	(4.29) ***	(3.31) ***	(1.47)
Vol	0.003	0.005	-0.003	-0.016
	(0.91)	(1.446)	(-0.914)	(-2.696) ***
AvgTS	0.012	0.003	0.007	0.002
	(1.81) *	(0.43)	(2.72) ***	(0.22)
Fixed Effects	Time	Time	Time	Time
Adjusted R^2	0.256	0.262	0.286	0.422
N	820	820	820	820

Note. This table contains the results of the panel regression analysis with time fixed effects and using an alternative measure of intra-market fragmentation, Frag (Other). Frag (Other) is the result of calculating the Herfindahl-Hirschman using exchange volume data and subtracting this value from 1. Frag (Other) is similar to Frag except it excludes market share data for the current exchange. Panels A and B contain data based on order books and transactions conducted in USD ($) and Euro (€), respectively. Results are calculated for each exchange using all transactions in a single currency over a single trading day over the sample period (1 January 2017 to 31 March 2019). MS is the exchange-specific market share, measured as a proportion of total volume. σ is the average 5-minute standard deviation in basis points. BASp is the average quoted spread on the exchange. Vol is the total USD/Euro volume (reported in millions) of Bitcoin (BTC) transactions and includes both in and out-of-sample exchanges. AvgTS is the average size of each transaction in the exchange, measured in its respective currency (USD/Euro). σ, BASp, Vol and AvgTS have been transformed using the natural logarithm (ln). T-statistics can be found in parentheses below each regression coefficient. *,** and *** identify results of 90%, 95%, and 99% statistical significance, respectively. Information on the relevant fixed effects, adjusted R^2 and number of observations are also reported.

As a result, fragmentation negatively impacts the uninformed investors as the informed take advantage of satellite exchanges to cream-skim the most profitable orders, leaving behind trades executing at less favourable prices. This notion of cream-skimming is consistent with results reported Easley et al. (1996) and Bessembinder and Kaufman (1997)and with the findings presented in Chapter 3 surrounding dark pools. Regression results show that an exchange's information share is positively related to its bid-ask spread. The concentration of informed activity, and the resulting increase in information asymmetry, lead to wider bid-ask spreads as investors attempt to protect themselves against increased risk resulting from exposure to more investors with superior information.

Table 4-11 provides additional support for the H4-2 and H4-3. It contains a variant of the *Frag* measure, *Frag (Other),* which measures fragmentation in the market using only competing BTC exchanges. Therefore, it excludes the impact that the current exchange has on the structure of the market. Once again, *MS* coefficients are positive and range from 0.071 to 0.367 across USD and Euro exchanges. All coefficients are significant at the 1% level except for the European Exmo order book. Due to this, the European Exmo coefficient is excluded from the reported *MS* coefficients above. *Frag(Other)* coefficients are all positive and range from 0.011 to 0.616. Once again, the coefficients for *MS* and *Frag (Other)* are larger for more active exchanges.

In summary, increased market fragmentation either leads to an increase in the concentration of informed investors on the dominant exchange or the introduction of informed investors on smaller satellite exchanges. As a result, investors can no longer look towards a single exchange to gather all relevant price adjusting information. Further, the process of price discovery which entails forming an accurate opinion of price levels becomes more difficult as a market becomes more fragmented. Investors protect themselves against the risk of information asymmetry and adverse selection by widening bid-ask spreads, leading to a degeneration of market quality factors such as bid-ask spreads. The widening of bid-ask spreads is seen as a negative outcome to fragmentation as it increased the cost of a round-trip transaction for investors.

4.8 Summary of Results

The results of the hypothesis testing are summarised in Table 4-7. The study tested six main hypotheses some with multiple sub parts. The analysis and results support all of the hypothesised relations. However, due to the assumption tests in Section 4.5.4.4, the final coefficients may be affected by the presence of multicollinearity in the independent variables.

Table 4-12: Summary of Hypothesis Testing and Results

Hypothesis	Result Table	Conclusion
H4-1: When multiple exchanges offer the ability to transact in the same asset, price adjusting information is spread across multiple exchanges and does not originate from a single source.	4-8	Accept
H4-2: Market share is positively related to the informational content of prices on an exchange.	4-9 4-10 4-11	Accept
H4-3: Market fragmentation is positively related to the informational content of prices on an exchange.	4-9 4-10 4-11	Accept
H4-4: USD (Euro) exchanges contribute more information to USD (Euro) transactions than Euro (USD) transactions.	4-8	Accept

4.9 Conclusion

This study investigates the applicability of equity-based principles to instances of competitive market fragmentation in a relatively new asset class, cryptocurrencies. Using transaction and order-book data on the most dominant cryptocurrency, Bitcoin, it follows de Jong et al. (2001) and calculates a multivariate version of Hasbrouck's (1995) information share. The results confirm that an exchange's market share and the level of competitive fragmentation are positively related to the informativeness of exchange prices (Madhavan, 1995).

Consistent with the previous equity market study reported in Chapter 3, the result is explained by the migration of informed investors to competing exchanges. This, in turn, increases events of information asymmetry as individual exchange transaction prices become more informative. However, as permanent price-adjusting information is dispersed across an increasing number of exchanges, gathering all relevant information surrounding asset prices becomes more difficult and the price discovery process deteriorates. These results support the findings of Chapter 2 which presents a taxonomy of market fragmentation in Figure 2-12. Innovations that leads markets to fragment are altruistically motivated in their desire to reduce information asymmetry among investors. However, the reality is quite the opposite. Much like the fragmenting events in equity markets presented in Chapter 3, fragmentation in cryptocurrency markets increases levels of information asymmetry in the market. Benefits experienced by informed investors are a direct result of the increases in information asymmetry uninformed investors are subject to.

Chapter 5: Conclusions and Implications

This chapter summarises the results of the thesis and presents the overall conclusion of the research. Section 5.1 discusses the motivation behind the thesis and briefly summarises the major findings. Section 5.2 reports the key results of the thesis and provides a summary of its contributions to the field of research. Section 5.3 discusses the theoretical, practical, and educational implications of the thesis. Section 5.4 identifies the limitations of the results presented in the thesis. Finally, Section 5.5 suggests directions for future market fragmentation research.

5.1 Summary of Research

This research examines fragmentation in financial asset markets. Market fragmentation is traditionally a result of increased competition among providers of various products and services. Competition is viewed as an integral component of a healthy market. This is evident in governments' establishment of anti-trust policies that prevent monopolies in various financial, product, and service markets. The goal of this thesis is to explore various forms of fragmentation in financial asset markets and test whether current levels of competition are beneficial for investors. In particular, this thesis tests whether competition impedes or supports a market's ability to accurately price assets. Accurate pricing is important to investors as they are more likely to participate in markets whose prices are efficient and incorporate all publicly available information.

This thesis focuses on understanding the motivating factors that influence the fragmentation of financial asset markets. It aims to identify patterns in the motivations behind different forms of market fragmentations as well as the degree of innovation they entail. It also establishes a relationship between similar events of market fragmentation within various financial asset classes. A desire to test the connection between established theory on market microstructure and its implications for the price discovery process is also a motivating factor behind the research.

This thesis begins with a study of the innovations that cause markets to fragment. The initial study categorises multiple forms of market fragmentation. It then builds upon the work of Avlonitis et al. (2001) and Tufano (1989) to develop a taxonomy explaining the motivating factors behind key fragmenting events. It introduces 'pricing' into the taxonomy as a new, externally driven and temporal, fragmentation event. The taxonomy proposes that reductions in transaction costs play a primary role in motivating innovations that lead to an instance of competitive and substitutionary fragmentation in traditional financial assets. Regulatory changes are also a significant factor in market fragmentation, particular in equity markets. Reductions in asymmetric information either play a supporting role or are viewed as a consequence of market fragmentation. Technological shocks, regulatory changes and globalisation are responsible for more recent fragmenting events involving dark pools, cryptocurrencies, and high-frequency trading.

Next, the thesis selects one of the key motivating factors, reductions in information asymmetry or price discovery, and empirically explores its connection to market fragmentation. Equity and cryptocurrency markets are chosen as the setting for empirical research due to their abundance of competitive fragmentation events. Equity markets represent more traditional studies and contain a wealth of existing research which can be applied to the study. On the other hand, cryptocurrency markets allow for testing of the efficacy of equity-based market microstructure research in relation to a relatively new financial product.

This research examines whether the microstructure of equity and cryptocurrency markets relates to the informational content of exchange prices and/or mid-quotes. It also examines whether increased fragmentation in order books leads to greater difficulty in consolidating all permanent price adjusting information and thus impedes the price discovery process.

The Herfindahl-Hirschman Index (HHI) is used for the first time in studies of this nature in order to measure the construct of each respective market. Traditional measures of fragmentation such as market share are also used, but unlike HHI measures, they only indicate the popularity of a particular exchange or type of exchange. HHI provides a better measure of the structure of the overall market as it takes into account the extent to which investor activity is dispersed across multiple exchanges.

The first empirical study focuses on competitive market fragmentation in equity markets, and tests established research principles surrounding rational expectations theory and the efficient market hypothesis. The study uses Hasbrouck's (1995) information share and Gonzalo and Granger's (1995) component share as the primary measures of the informational content of exchange trade prices and mid-quotes. Results support existing theory on price discovery in equity markets and show that lit exchange trade prices contain substantially more information than dark exchange trade prices (Zhu, 2014). Both lit and dark forms of fragmentation incentivise the migration of informed trading to satellite lit exchanges. This has negative implications on the price discovery process as markets must consolidate information from multiple exchanges in order to maintain efficient price levels.

The second empirical study investigates the applicability of equity-based research principles to instances of competitive market fragmentation in a relatively new asset class, cryptocurrencies. Using transaction and order-book data on the most dominant cryptocurrency, Bitcoin, it follows de Jong (2001) and calculates a multivariate version of Hasbrouck's (1995) information share. The results confirm that an exchange's market share and the level of competitive fragmentation are positively related to the informativeness of exchange prices (Madhavan, 1995). Consistent with the previous equity market study, the result is explained by the migration of informed investors to competing exchanges. This, in turn, increases events of information asymmetry as individual exchange transaction prices become more informative. However, as permanent price-adjusting information is dispersed across an increasing number of exchanges, gathering all relevant information surrounding asset prices becomes more difficult and the price discovery process deteriorates.

In summary, the empirical results suggest that competitive market fragmentation is detrimental to the price discovery process. While competing exchanges primarily attract uninformed trading, some informed investors leave the dominant exchange as well. Doing so, they take with them important information that contributes to the accurate pricing of financial assets. This makes it more difficult for the market and its investors to compound all price adjusting information into asset prices, thereby impeding price discovery. The results also suggest that while competitive market fragmentation is partially motivated by the desire to reduce information asymmetry, the result is often the opposite. Information asymmetry increases as some informed investors follow the uninformed to competing exchanges in order to capitalise on their informational advantage. As uninformed investors migrate to competing exchanges, the proportion of informed to uninformed trading increases on some exchanges and also contributes to increased levels of information asymmetry. Finally, consistencies in the results between equity and cryptocurrency markets suggest that established equity-based theories apply to alternate financial assets markets.

5.2 Conclusions to Research Questions

This section discusses the main findings in detail and relates the hypothesis testing and results back to the initial research questions identified in Chapter 1. The first research question asks:

RQ1: What are the motivating factors that lead to the fragmentation of financial markets?

The taxonomy in Figure 2-12 proposes that reductions in transaction costs play a primary role in motivating innovations that lead to an instance of competitive, fragmentation based on customer type, and substitutionary fragmentation in traditional financial assets. Reductions in asymmetric information either play a supporting role or are viewed as a consequence of market fragmentation. Technological shocks, regulatory changes and globalisation are responsible for more recent fragmenting events involving dark pools, cryptocurrencies, and high-frequency trading. The introduction of the Markets in Financial Instruments Directive (MiFID) in November of 2007 increased levels of competitive market fragmentation among lit (quoting) and dark (non-quoting) equity markets. Technological shocks also acted as a catalyst which led to the formation of new exchanges and financial asset classes, notably cryptocurrencies. The results also show that competitive market fragmentation leads to the development of products which modify existing offerings. Fragmentation based on customer type lead to extensions of existing offerings and substitutionary fragmentation is responsible for the development of completely new innovations.

The remainder of the discussion focuses primarily on the empirical results from the studies reported in Chapters 3 and 4. Research questions 2 and 3 are explored in Chapter 3 and 4 respectively. They are as follows:

RQ2: How does competitive market fragmentation affect the equity market's ability to efficiently price assets and convey price disseminating information to the public?

RQ3: How does competitive market fragmentation affect the cryptocurrency market's ability to efficiently price assets and convey price disseminating information to the public?

The results show that both equity and cryptocurrency markets react similarly to changes in market microstructure. Fragmentation negatively affects both markets in terms of price discovery, which answers both RQ2 and RQ3. While activities on individual exchanges become more informative, the dispersion of information across multiple exchanges makes it more difficult to collect all relevant price adjusting information. This is a novel finding as it provides credibility to the application of established equity market research, notably the rational expectations theory and efficient market hypothesis, to non-equity assets. As a result, it supports the need for future studies that apply established theory to financial assets which lack a similar research pedigree. The remainder of this section discusses the key findings and how they relate to the empirical tests contained within this thesis. The key findings to Chapters 3 and 4 are outlined in Table 5-1

Table 5-1: Summary of Key Findings

Key Findings	Relevant Hypotheses: Equity (Chapter 3)	Relevant Hypotheses: Crypto (Chapter 4)
1. (A) Information that contributes to price discovery is found, to varying degrees, on all exchanges.	H3-3A H3-3B	H4-1
1. (B) Increased competition amongst exchanges attracts informed investors away from traditional exchanges.	H3-4A H3-5A	H4-2A
2. Competing exchanges attract proportionally more uninformed investors than informed investors.	H3-5B H3-6B	H4-3
3. Mid-quotes are more informative than transaction prices. Their importance increases with greater levels of competition amongst exchanges	H3-2A H3-2B	
4. Trades in pre-trade transparent (lit) exchanges contain more information than trades in dark exchanges.	H3-1 H3-6A H3-6B	

The first key finding is that permanent, price adjusting information is found on all exchanges (Table 5-1 - 1A). The study finds support for H3-3A and H3-3B that consolidated markets, consisting of all exchanges which transact in a particular asset, contain more information than the dominant exchange. This implies that informed investors have an incentive to venture away from their historical trading venues. Unfortunately for price discovery, they take with them valuable information and make it more difficult to compound into prices all relevant information. This is not only true for equity investors, but cryptocurrency investors as well according to results for H4-1. The implication is that investors behave similarly, regardless of the asset they are trading, when faced with varied levels of competition amongst the exchanges in which they can trade.

This is further evident in key finding 1B which states that competing exchanges attract some level of informed trading. H3-4A (H3-5A) state that increased levels of competition among (non) quoting exchanges deteriorates the quality of price information on the primary exchange. This is again explained by the migration of informed investors to alternative trading venues. Exchanges that entice investors to trade within their order book will attract some level of informed trading. The argument is that informed investors use these new markets to spread around their orders to better conceal any information that may be extracted from their transactions (Mendelson, 1987). H4-2A provides validation that informed investors behave similarly regardless of the asset class in which they are trading. This associated with higher levels of adverse selection in the lit market and is consistent with the notion that the most profitable uniformed trades are being 'skimmed' by informed liquidity providers (Bessembinder & Kaufman, 1997; Easley et al., 1996).

The second key finding states that exchanges attract proportionally more uninformed investment trades than informed ones. Results support H3-5B and H3-6B which state that competition among exchanges, regardless of their pre-trade transparency requirements. This concentrates informed trading on some exchanges and improves the quality of their price signals. Exchanges cannot support exclusively informed trading as it would reduce the probability of execution. Informed investors trades are positively correlated with the value of the asset and, as a result, would cluster on the heavy side of the market (Zhu, 2014). Uninformed transactions, however, are more likely to find a counterparty to their trade as they can transact against informed and uninformed orders. Once again, H4-3 shows that this phenomenon is not unique to equity investors.

The third key finding proposes that not only are mid-quotes more informative than transaction prices, but they also become increasingly more informative as markets fragment. The results of H3-2A and H3-2B support this finding. Fragmentation, both within and across markets, encourages informed investors to congregate on quoting exchanges while uninformed investors opt for trading in dark pools. While this improves the quality of the information in lit markets, it comes at the cost of increased adverse selection risk. Under such conditions, informed investors prefer to supply liquidity due to their informational advantage and target the most profitable uninformed trades. The final key finding proposes that trades in pre-trade transparent markets are more informative than trades in dark pools is supported by the outcome of H3-1, H3-6A and H3-6B.

The findings coincide with the results modelled by Zhu (2014) and show that the migration of trades from lit to dark markets (inter-market fragmentation) is predominately uninformed. By disproportionally attracting uninformed investors, inter-market fragmentation increases the overall quality of the information in lit exchanges. Unfortunately, this comes at the cost of greater adverse selection risk as investors face more sophisticated competition. This encourages informed investors to use their informational advantage to supply liquidity to the market and benefit from less-informed investors in lit exchanges (L. Ye, 2016).

In summary, increased market fragmentation either leads to an increased in the concentration of informed investors on the dominant exchange or the introduction of informed investors on smaller satellite exchanges. As a result, investors can no longer look towards a single exchange to gather all relevant price adjusting information. Therefore, the process of price discovery, that is, the process of forming an accurate opinion of prices levels, becomes more difficult as market fragmentation increases. This occurs as investors protect themselves against the risk of information asymmetry and adverse selection by widening bid-ask spreads, leading to a degeneration of market quality factors such as bid-ask spreads. The widening of bid-ask spreads is seen as a negative outcome to fragmentation as it increased the cost of a round-trip transaction for investors. The results show that the popularity of dark pools (inter-market fragmentation), as measured by market share of dark pools, is positively related to dark market fragmentation. Competition among dark pools increases when there is significant liquidity to support multiple exchanges. Liquidity must be largely uninformed as informed traders are more likely to congregate on the heavy side of the market. This exposes informed investors to increased levels of non-execution risk since they cannot locate enough uninformed liquidity against which to transact. As a result, informed investors continue to prefer trading in the lit exchanges and by doing so increase the quality of information on those exchanges at the cost of greater adverse selection risk.

5.3 Implications of the Research

The findings entailed in this thesis have several implications for future theory, practice, regulatory policy, and education.

5.3.1 Implications for Theory

This research makes a theoretical contribution by establishing a taxonomy for market fragmentation. It builds upon Avlonitis et al. (2001) and Tufano (1989) and introduces the three P’s of market fragmentation: process, product, and pricing. Unlike process and product events, fragmentation in pricing is an externally driven event that results from the deviation of established equilibrium prices. It is the only externally driven form of fragmentation and, unlike the others, is a temporary reaction to market conditions. The research also shows that process-based fragmenting events stem from the modification or extension of existing services. However, product-based events result in new offerings that are unlike what is currently available in the market. Also, reductions in transaction costs play a dominant role in motivating innovation which leads to market fragmentation.

This research also makes a contribution to existing research by applying market microstructure theory to price discovery in equity markets. The findings validate Zhu (2014) and confirm that informed investors use lit markets, as opposed to dark pools, for the majority of their transactions. It also confirms existing research that increased fragmentation leads to greater information asymmetry, thereby exposing uninformed investors to greater adverse selection risk (Chowdhry & Nanda, 1991; Madhavan, 1995). As a reaction to greater risk exposure, and to deter informed investors from 'cream-skimming' the most profitable trades, markets react by widening bid-ask spreads (Easley et al. (1996); Bessembinder and Kaufman (1997)).

The research also implies that existing equity-based theories surrounding rational expectations theory and the efficient market hypothesis apply to cryptocurrency markets. Fragmentation measures such as market shares and the Herfindahl-Hirschman index, when combined with established informational measures, lead to similar results in both equity and cryptocurrency markets. This implies that informed investors react similarly to changes in market microstructure regardless of the financial asset in which they are investing. This is a novel finding and opens the possibility for the use of other equity-based theory in relation to cryptocurrency markets.

5.3.2 Implications for Policy and Practice

This research implies that increased competitive market fragmentation results in the degradation of an investor's ability to formulate accurate prices. With price-adjusting information spread across multiple exchanges, gathering all the information necessary to construct accurate prices becomes more difficult and costly. This means that investors trading in consolidated markets, where the number of exchanges in which they can transact is kept to a minimum, will find it easier to identify and incorporate information contained within transaction prices.

Since consolidated markets are more efficient and more accurately convey prices that resemble the true value of the assets, they are more supportive of uninformed trading. This means that less sophisticated investors will find it easier to trade in consolidated markets since the advertised prices in these markets are more accurate. However, more sophisticated and informed investors will find it more profitable to trade in fragmented markets. Fragmented markets make it easier for informed investors to conceal the intentions behind their trades. Protecting private information is important to informed investors as it provides them with compensation for taking on the responsibility of gathering costly information. Since it is more difficult to distinguish between superior information and noise in fragmented markets, informed investors can use these markets to better leverage their superior information.

The results surrounding market fragmentation are also important from a regulatory standpoint. As mentioned in Chapters 2 and 3, recent regulatory changes in Europe, such as the Markets in Financial Instruments Directive (MiFID), have a significant influence on the level of competitive market fragmentation. European equity market investors are increasingly relying on alternatives to the primary exchange, such as multilateral trading facilities (MTFs), to conduct transactions. Many of these venues report the results of successful transactions independently. Very few exchanges, most notably dark pools, report their transactions to a central consolidated tape. This makes collecting permanent price-adjusting information more difficult as investors must have access to, and consolidate transaction results across many exchanges to help markets maintain accurate prices levels. The lack of a published consolidated order book also means that incorporating relevant quote data into transactions prices is also more difficult. As a result, there is a greater margin of error in advertised and historical trade prices. This opens regulatory agencies to a debate about whether policies must be put in place to provide investors with a more centralised source for trade and order book information.

Policies regarding more centralised access to trade and order book information are also relevant with regards to levelling the playing field between retail and institutional investors. Institutional investors are viewed as more sophisticated with regards to their ability to gather superior private information as well as access multiple exchanges simultaneously with the aid of computer software. While little can and should be done surrounding the generation of private information, the results in this thesis open the floor to a debate about whether retail investors should have more access to tools which source liquidity from multiple exchanges. Compensation for costly information gathering is a reward to informed investors for their contribution to market efficiency. However, informed investors receive additional benefits because they afford to invest in told that allow them greater access to liquidity. The question remains as to whether institutional investors are deserving of greater access to liquidity, compared to retail investors, simply because they are more likely to be able to afford it. If regulators do not intend to provide retail investors with the same accessibility to liquidity that institutional investors can afford, then this leads to the question of whether governments should play a role in restricting the number of exchanges.

Finally, there are currently no government-mandated reporting policies for cryptocurrency exchanges. The results of this thesis show that cryptocurrency markets are similar to equity markets in the way they react to fragmenting events. As investment in cryptocurrencies continues to grow, the results imply that regulatory bodies should include cryptocurrency exchanges in their discussion of trade reporting and investor protection policies.

5.3.3 Implications for Education

Stable environments provide little insight into the nature of financial market forces as very little changes when markets are at an equilibrium. At a minimum, before and after snapshots are necessary to measure change and the effect the change has on markets. Luckily, the past two decades contain a plethora of fragmenting events. These events stem from changes in regulations, advancements in technologies, and opportunities to establish a foothold in the market by offering investors an incentive to migrate across trading platforms. The more dynamic nature of fragmented markets provide opportunities and cases through which students can observe and discuss concepts like the asymmetry of information, information flows, price formation, 'cream-skimming', informed vs uninformed investors, the role of liquidity and the role and impact of regulation.

The taxonomy presented within this thesis will help students better recognise the driving forces behind market fragmentation. Understanding the motivational factors behind innovations that lead to market fragmentation allows students to understand why such changes are necessary. It will also help them identify gaps in existing process and product offerings allowing them to anticipate potential future market microstructure changes.

The results also open the debate for the efficacy of increased competition in markets. Economics and finance texts propose that monopolies lead to unfavourable conditions for investors and competition can help improve these conditions. However, this research proposes that educators should question whether unlimited competition is beneficial under all circumstances. In fact, the results open the debate for the benefits of controlled competition in the absence of sufficient investor protection policies. In financial asset exchanges, increased competition leads to the dispersal of price-adjusting information. This leads to less efficient pricing in financial assets. Therefore, unrestricted competition negatively impacts market conditions by increasing transactions costs and exposes investors to greater asymmetric information risk. This implies that educators should be more cautious when promoting the benefits of competition as more choice does not always improve conditions for investors.

5.4 Limitations

The results presented in this thesis are partially limited by the scope of the data used. Chapter 3 collects data on the top twenty stock across six countries to construct a European dataset that more closely resembled the cross-border nature of European equity trading. However, the inclusion of additional stocks from the sample countries would further contribute to the generalisability of the results. As would incorporating stocks from countries that are outside of the sample. Smaller stocks and stocks from smaller countries are likely to exhibit different properties in fragmented markets due to the thinner information environment for these stocks. Expanding the scope is a potential avenue for future research.

A similar argument regarding the scope of the dataset can be made for the cryptocurrency study in Chapter 4. This study would benefit from the inclusion of additional cryptocurrencies, such as Litecoin and Peercoin, to test whether the results are robust across multiple cryptocurrencies. The cryptocurrency study is also limited to trades in USD and Euro. However, the Japanese Yen is the second most active sovereign currency used in Bitcoin trading as of March 2019 (see Figure 2-7). Also, this study focusses on independently operated exchanges. However, as shown in Figure 2-6, the peer-to-peer market where users trade Bitcoin directly with each other is the most active type of exchange as of March 2019. Peer-to-peer exchanges do not operate using a limit order book and do not employ broker-dealers. Instead, they more resemble the over-the-counter market where customers negotiate trade prices directly with each other. Nevertheless, a future study of the informational content of such trades could prove insightful.

The study in Chapter 3 could also benefit from a wider time-frame. In particular, data before the introduction of MiFID on 1 November 2007 would allow for a study of market conditions when fragmenting events were less common. This period also represents a more consolidated market structure and would allow for better juxtaposition against periods of increased fragmentation.

The equity study, in Chapter 3, also ignores any transactions reported to the consolidated tape which do not explicitly identify the exchange in which the trade took place. While this means that some dark liquidity transactions are ignored, it leads to a more accurate measure of fragmentation as we do not have to employ a proxy to distribute the volume from non-exchange specific transactions to specific exchanges. Future studies could explore the information content these more opaque dark trades.

Finally, the results of Chapters 3 and 4 are subject to some distortion due to the presence of moderate levels of multicollinearity. However, in Chapter 4, most of the multicollinearity exists among the control variables as opposed to the key fragmentation regressors.

5.5 Future Research

Future research can begin by addressing the limitations presented in the previous section. Increasing the breadth and depth of datasets would allow for greater generalizability of the results. It would also allow for more opportunities for comparison across time and assets.

Researchers could expand on the studies in Chapters 3 and 4 to allow for non-linearity in the key measures of fragmentation. Studies such as Degryse et al. (2015) and Comerton-Forde and Putniņš (2015) identify that fragmentation improves liquidity and price discovery, respectively, so long as the market share of dark pools does not exceed 10%. Expanding the model to test for the non-linear nature of HHI based fragmentation measures would provide insight into the ideal level of competition across a market, rather than two competing exchanges. This information would be helpful for regulators in establishing policies that potentially improve retail investor access to liquidity originating from multiple exchanges.

Corbet et al. (2018) study the direction and intensity of informational spillovers across assets, including various cryptocurrencies. Future research would benefit from testing whether a particular cryptocurrency's market microstructure influences the value of substitute cryptocurrencies. These results would allow researchers to gain insight into whether cryptocurrencies uniquely establish their prices of if their prices are influenced by competing cryptocurrencies. If the research resulted in a single cryptocurrency as the information leader, it would imply that investors need only monitor one cryptocurrency market to gain an accurate representation of the value of all competing cryptocurrencies.

While Corbet et al. (2018) study the spillover across different cryptocurrencies, they do not isolate for the effects of the different fiat currencies used in the transactions. Further research could help identify which fiat currency, if any, leads the market as a source of permanent price-adjusting information. This would have significant implications regarding the breadth and scope of information investors must observe to determine efficient price levels.

Finally, both of the empirical studies presented in this thesis can be improved by allowing for directional testing within their hypotheses. As it stands, the study can only identify the presence of positive and negative relationships between fragmentation and price discovery. By improving upon the model, future research can prove that fragmentation leads to changes in the informativeness of prices in exchanges or vice versa.

In conclusion, a broader question to consider is can the lessons from this study of fragmented financial asset markets be applied to the price formation and information content in other assets markets. For instance, are fragmented commodity markets, like gold or other resources, optimal or suboptimal in terms of information asymmetry and price determination? There is a potential for a program of research into different market fragmentation stemming from the current thesis.

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Appendices

Appendix 1: Dark Pools

A1.1 Dark Pools

Dark pools are trading venues that, unlike traditional exchanges, do not post bid and ask quotes.

A1.1.1 Public Crossing Networks

Public crossing networks are the most traditional of all dark pools. They are the pools to which most buy-side firms connect and typically form when agency-only brokerage firms seek alternative sources of revenues, such as commissions. A key feature of public crossing networks is that client orders do not interact with those of the dark pool operator. Public crossing networks rely on their ability to offer liquidity through a unique model, which can be difficult, and as a result have seen few entrants over recent years.

Public crossing networks generally match orders on a continuous basis, that is, as orders arrive, without conveying an investor's buy or sell intentions to anyone. However, there does exist a subset of firms that match orders based on advertisements. In these advertisement-based pools an alert goes out to the traders informing them of a potential match. Systems vary in the way alerts are sent. In some cases, both sides receive an alert for the potential match and neither party is committed to the order. In other cases, one side will be committed while the party who receives the alert has the option of whether or not to execute the trade.

Major public crossing networks include POSIT, Instinet, and Liquidnet, which are some of the first entrants into market.[40]

A1.1.2 Internalization Pools

Internalization pools are designed to internalize an operator's trade flow. Their purpose is to save the trading venue money by allowing orders to be crossed internally rather than sent outside to external trading venues and incurring transaction fees. Internalization pools are also operated by buy-side firms as a means of generating additional commissions. The primary difference between internalization pools and public crossing networks is that internalization pools allow for client orders, from both retail and institutional clients, to interact with the proprietary order flow of the operator.

Major internalization pools include Credit Suisse's Crossfinder and Goldman Sachs' Sigma X.

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[40] This supports the previous statement that there have been few new entrants classified as Public Crossing Networks.

A1.1.3 Ping Destinations

Ping destinations are, in some ways, the complete opposite of public crossing networks. Client orders interact exclusively with the owner's propriety order flow as opposed to with each other, making the Ping Destination a new form of market-maker. They are also quite unique in the sense that they only accept Immediate or Cancel(IOC) orders, which require interaction with venue owned shares. If only client trades were crossed then the probability of execution would be extremely low due to the unlikelihood of two opposing orders entering the pool at the exact same time.

Ping destinations rely on quantitative models operating in a black box to make decisions as to whether or not to accept an IOC order. The majority of their customers are sell-side firms that use dark pool aggregators or Smart Order Routing Technology (SORT) to locate sources of liquidity.

A1.1.4 Exchange Based Pools

Two sources of dark liquidity are combined in this category as they share many defining characteristics. The first are dark pools that are registered as MTFs by the operating exchange and include Turquoise Dark and Xetra Midpoint. The second are implicitly created pools formed as the result of the introduction of hidden order types on the operating exchange. Hidden orders differ from iceberg or reserve orders in that not even a portion of the order is made visible on the lit exchange, thus preventing any changes to displayed quotes.

A1.1.5 Consortium Pools

Consortium pools differ from the aforementioned venue classifications in that they are established by a group of partnering brokers. They are similar to public crossing networks except they are not typically run by agency-only firms. They also resemble internalization pools except they are established as separate organization, and as such fall under regulatory guidelines that require for increased transparency in their activities.

A1.2 Are They New?

While the dark pool as a distinct venue may be a new phenomenon the concept of 'dark' or 'hidden' liquidity is not new. Reserve/Iceberg orders predate dark pools and allow investors to submit large volume orders to the market in increments while publicly displaying only a specified portion of the total order size. Reserve/Iceberg orders, however, are not entirely hidden because a portion of the order is still made public. Hidden order types are also a historical transaction type that allow for dark liquidity within a lit order book. Other forms of dark liquidity include floor broker orders and specialist capital on floor-based exchanges, working orders handled by agency brokers or broker-dealers, dealer capital and stand-alone as well as broker and exchange/ECN operated crossing networks (Buti et al., 2011).

Dark pools as a separate entity are also a decades old phenomenon. However, it is only recently that they have been absorbing a significant market share of order flow, thus gaining attention on a global scale (Degryse et al., 2009). Crossing networks originate from the early 1970s and consist of phone-based networks between buy-side traders. Though we must note that the liquidity being provided is not completely dark as the broker requires knowledge of the transaction in order to find a counter-party. Nevertheless, since the intentions of the parties are not made public until after the trade is completed, they, like upstairs market transactions, are still considered a source of dark liquidity. In the 1980s electronic networks such as Instinet and POSIT were introduced which eliminated the need for human interactions and thus improved the anonymity of crossing network transactions.

There are currently over 40 dark pools operating separately in both the U.S. and in Europe with consolidated market shares of 14.4% and 33%, respectively.[41] Their recent growth is attributed to the introduction of new regulations, such as RegNMS in the U.S. and MiFID in Europe, that result in an environment that is more conducive to the formation and expansion of alternative trading venues. Growth in the popularity of dark liquidity is also attributed to improvements in technology, such as algorithmic order routing, which directs order flow to various trading venues while protecting investors' interests by taking into account prices, liquidity, and market impact, among other variables. (Degryse et al., 2009)

A1.3 Vs. The Over-The-Counter/Upstairs Market

The upstairs market, also known as the over-the-counter-market, refers to when trading occurs within a broker-dealer firm as opposed to a traditional exchange. Upstairs market trades, like those originating from dark pools, are protected under regulatory policy and subject to the best-execution rule. This rule stipulates that prices given to customers must not be less favourable than those offered to investors by visible order book operators. As a result, the best-execution rule states that prices must fall within best bid and ask spread of the primary or consolidated market.

[41] Values sourced from Rosenblatt Securities Inc. (http://rblt.com/news_details.aspx?id=217)(U.S.) and the Financial Times (http://www.ft.com/cms/s/0/f1142a76-322a-11e2-b891-00144feabdc0.html#axzz2L7xhct7b)(Europe).

The main difference between the two trading venues is that dark pools operate using an electronic trading system which requires no broker or dealer involvement, resulting in complete pre-trade transparency. Since dealers in the upstairs market contact other dealers in order to source liquidity there is potential for some information leakage. In his paper 'Do Dark Pools Harm Price Discovery?' {Zhu, 2014 #432}Zhu (2014)acknowledged that although this type of liquidity is not usually classified as dark, it is still a source of non-displayed liquidity. Another difference between dark pools and the upstairs market is said to be the trading cost, which is theoretically lower in dark pools (Lefebvre, 2010).

A1.4 How are Transactions Executed?

The following illustrates the steps involved in completing a transaction within a dark pool: [42]

i. The trader who would like to buy/sell the security calls his broker or places an order over the electronic system of the broker.
ii. The broker internalizes the order and looks for suitable matches within his network. This work is sometimes done by computer algorithms which can break the order up into several pieces and locate the most appropriate venues for executing the transactions.
iii. The transaction details are forwarded to clearing and settlement houses.
iv. The confirmation of the trade and trade details are then provided to the two parties.

A1.4.1 Matching Frequency

Dark pool orders can be matched in the following ways:

Continuous cross: Orders are matched as they enter the system.

Periodic cross: Orders are processed in batches at pre-determined times throughout the day. These are among the first types of dark pools. Over time companies began offering more frequent crossing opportunities until they finally began offering continuous crossing. Posit Match is an example of an existing periodic crossing pool.

Advertisement based: Alerts are provided to one or both parties of the transaction. Systems vary in the way alerts are sent. In some cases both sides receive an alert for the potential match and neither party is committed to the order. In other cases one side will

[42] Steps sourced from (Achuthakumar, 2009).

be committed and the party who receives the alert has the option of whether or not to execute the trade.

A1.4.2 Price Determination

Regulatory policy, specifically the best-execution rule, dictates that transactions in a dark pool environment cannot be executed at a price that is less favourable than that offered to customers of traditional exchanges. As such, transactions are executed at a price referencing one of the following:

National Best Bid and Offer (NBBO) (U.S.) - The best bid and ask prices as determined by the consolidated national market.

Primary Best Bid and Offer (PBBO) - The best bid and ask prices as determined by the exchange of primary listing.

European Best Bid and Offer (EBBO) – The best bid and ask prices as determined by the consolidated European market.

While the NBBO is the standard in the US, European dark pool operators have the option of referencing either the PBBO or EBBO. Originally most operators referenced the PBBO however recent trends have shown that there has been a preference to switch to the EBBO.[43]

Though all pools allow for trades to be executed at the midpoint, some venues also allow transactions at the best bid or best ask. The benefit from executing at the best bid/ask is increased probability of execution by moving towards a price for which an outstanding limit order may exist. This strategy is most effective when there are no orders at the midpoint but plenty of limit orders are available at a higher ask/lower bid price. In order to further cater towards the heterogeneous needs of investors some pools have also allowed for more specific transaction pricing. For example, a trader who wishes to purchase stock but does not place significant value on immediacy can specify ‘midpoint-1 cent’. On the other hand, a trader who values immediacy can place an order at ‘midpoint+1 cent’ and increase the probability and speed of finding a match. In most cases investors can also specify a limit price in order increase the probability of execution (Ray, 2010).

[43] See ‘Instinet first to float EBBO’ (http://www.thetradenews.com/newsarticle.aspx?id=8293).

Prices are generally decided upon after a match has been made. An order enters a dark pool and either immediately or after some time finds a counter-party to the trade. At that point the electronic system references the designated BBO and decides upon a price for the transaction. There are some instances in which prices are determined before the match has been made. Instinet, for example, operates a closing cross that matches orders at the closing price. However, in order to prevent predatory trading, it closes crosses for any company that makes an announcement after markets have already closed (M. Ye, 2012).

A1.4.3 Types of Orders

Dark pools allow for the use of the following order types:

Market order – The order is filled in reference to the prevailing BBO.

Limit order – The order is filled at a price no worse than the customer specified limit in reference to the prevailing BBO.

Immediate or Cancel (IOC): The order is either filled in its entirety, in reference to the prevailing BBO, or removed from the liquidity pool. Many dark pools no longer allow this feature as it can be used for gaming purposes to try and detect available liquidity.

A1.4.3.1 Order Attributes

The following is a list of key trade attributes that modify the order type:

Mid-Point: The order is pegged to the prevailing mid-price of the NBBO/EBBO/PBBO quote.

Pegged order: The order is pegged to any point inside the spread (e.g. bid, ask).

Minimum Quantity: The order cannot interact with orders smaller than this quantity for the first fill.

Persistent minimum quantity: The minimum quantity is forced throughout the life of the order and not just for the first fill.

Limit Price: Do not execute the order at a price inferior than the limit price.

Do not interact with: Exclude various counter parties including other dark pools or liquidity partners.

Send/Do not send IOI: Refrain from sending Indication of Interest messages to other dark pools or liquidity partners. These messages are used to find available liquidity from external sources. They do not often include information about the size of the order or whether the party is a buyer or seller. Many dark pools no longer allow this feature as it can be used for gaming purposes to try and fish out available liquidity.

A1.4.4 How is Liquidity Accessed?

Orders sent to a dark pool first interact with the resident dark order book. If the necessary liquidity is not available, they are then sent to either the proprietary lit order book, in the case of exchange based pools, or to the dark order books of partnering companies. In order to increase the probability of execution [44] for their clients many dark pool operators have developed liquidity sharing agreements with their competitors. The result is a mutually beneficial relationship which satisfies clients' needs for liquidity while maintaining a steady customer base that would otherwise be lost in the face of high rates of non-execution. Finally, if the order is still not filled the remainder is sent to the primary exchange. This type of strategy does require the client to have access to some Smart Order Routing Technology (SORT). [45] As such this is often feasible for institutional investors but not so for retail clients who could not financially justify the investment.

In order to maintain an acceptable likelihood of execution some dark pools have developed liquidity partnerships with competing trading venues, as mentioned above. [46] The result is that if an order cannot be completed on the proprietary dark order book it is immediately sent to the partnering order book. A key benefit of this is improved probability of execution for retail clients who do not have access to SORT. It has been estimated that up to 99% of a crossing network's transactions are crossed against clients' transactions from an external dark pool (Nimalendran & Ray, 2014).

[44] Probability of execution is found to be lower in a crossing network and has been noted as being one of the largest costs associated with dark liquidity trading (M. Ye, 2010).

[45] The increase in use of SORT technology (Hendershott & Riordan, 2013)in aggregating dark liquidity has resulted in participation rates of 15-25%(Altunata, Rakhlin, & Waelbroeck, 2010)).

[46] See article 'Instinet Europe joins TQLens' (http://www.tradeturquoise.com/press/instinet_europe_joins_tq_lens.pdf).

It should be noted, however, that investors often have the option to refrain from sending their orders to particular venues, including primary lit exchanges. The main reason for this is that some investors may want to refrain from transacting in what are known as 'toxic' pools.[47] Toxic pools are those that do not restrict the type of activity that occurs in the pool and, as a result, subject clients to predatory behaviour.

A1.4.5 Trade Reporting

In accordance with the post-trade transparency regulations of MiFID, trades must be reported within 30 seconds to a designated trade reporting facility (TRF), such as Markit BOAT, once the transaction has been finalised (Nimalendran & Ray, 2014). Dark pools have the option of allowing their identity to be known when reporting the transaction. If a pool chooses to refrain from reporting their identity the transaction will be flagged as either OTC or SI in the TRF's consolidated tape.

If a large order is executed in pieces the individual trades must be reported as they occur. Providing a minimum quantity with the order will therefore help prevent those interested in gaming from identifying that there may be a large order in the market as they are not likely to place large orders during 'fishing' expeditions.

Prior to MiFID, trades originating from dark pools would either be reported to a primary exchange, such as the Frankfurt Stock Exchange, [48] or would not be reported publicly at all. One of MiFID's key directives is to increase the level of transparency in the market and make sure that all trades are reported, though the identities of the reporting firm can continue to remain secret.

Unfortunately, allowing trade reporting firms to refrain from having their firm specified as the source of the transaction has introduced a degree of difficulty into academic research on dark pools. This inability to locate the source of the transaction has made it difficult to measure just how fragmented the market has become since the rise in the popularity of dark liquidity. While total dark volume can be measured it cannot be done on a trading venue by trading venue basis. According to Thomson Reuters Market Share Reporter, roughly 49% of the total dark trading activity in Europe cannot be traced to an originating venue.[49]

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[47] For additional information see (Mittal, 2008) – 'Are you playing in a toxic dark pool?'.

[48] See 'Liquidnet Europe signs up with Markit BOAT' (http://www.securitiestechnologymonitor.com/issues/19_61/22379-1.html).

[49] See link for more details (http://thomsonreuters.com/products_services/financial/financial_products/a-z/market_share_reports/).

Appendix 2: Features of Cryptocurrencies

A2.1 Features of Cryptocurrencies

This section describes some of the key features of virtual currencies, the broader category under which cryptocurrencies operate. When possible, characteristics that distinguish cryptocurrencies from the broader definition will be noted.

A2.1.1 Value

As mentioned previously digital currencies do not base their value in any sovereign currency. Much like commodities such as gold and oil they use the forces of supply and demand to determine value. Unlike commodities, however, they do not maintain any intrinsic value and are deemed worthless in the absence of a functioning exchange where their value can be transferred to another asset. This is due to the fact that digital currencies are not considered to be a financial obligation the firm issuing the currency.

Traditional forms of monetary policy do not apply within the scope of digital currencies and cannot be used to adjust the value of a given currency. Cryptocurrency schemes take things a step further and use computer algorithms to manage currency supply, thus not allowing for human intervention. Bitcoin, the most prominent form of cryptocurrency, maintains such a supply policy.

A2.1.2 Distributed Ledger

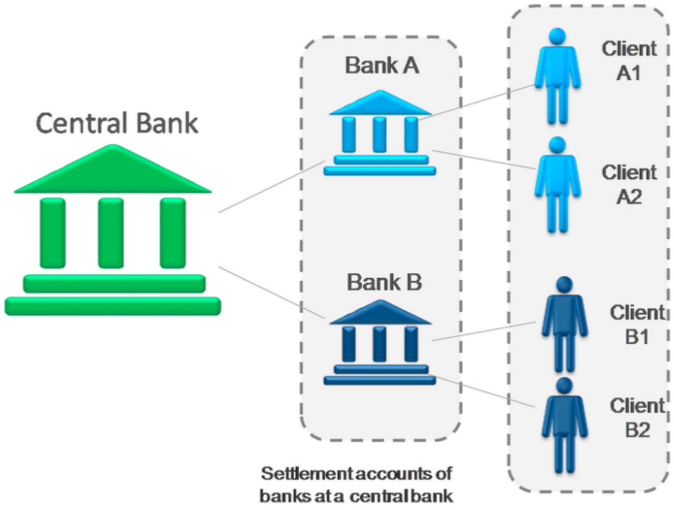
Outside of the determination of value, the next most prominent feature of digital currency schemes involves the process in which funds are transferred across parties. Prior to the establishment of cryptocurrencies, and distributed ledgers, the only way for two parties to exchange funds between each other without using a financial intermediary was to use cash. If you wanted to exchange funds between accounts you would need the support of both the central bank and at least one retail institutions; two retail institutions of the parties involved are members of different banks. The central bank is responsible for clearing and settling payment requests from its participants, though this step is only necessary in the presence of multiple retail outlets within the transaction. They maintain a central ledger and keep track of the balances of its members. Retail institutions must also adjust their own ledgers to reflect the changes resulting from the transaction. This system relies on the validity of these central ledgers and their ability to maintain an accurate account of transactions and protect against potential security breaches.

The distributed ledger is one of the pivotal technological developments that allows for the facilitation of peer-to-peer transactions, negating the need for a trusted third party. Rather than maintaining a central ledger in a single location a distributed ledger exists across many computers and servers worldwide and contains a complete history of the currency's transactions. Blockchain, a form of computing technology that utilises cryptography, is used to verify and validate the status of any given copy of the ledger in order to identify discrepancies and protect against fraudulent transactions. As multiple copies of the ledger exist worldwide data fraud for the purposes of theft is maintained to a minimum as fraudulent transactions can be identified when attempting the clear and settle the transaction.

Market participants have access to digital wallets in which to store currencies. When a transaction is initiated the payer's wallet will forward a series of cryptographic keys to the payee's wallet. The funds must then be verified before being added to the payee's wallet. Once the transaction has proven to be successful a record of the transaction is added to the general ledger, of which multiple copies exist on computers and servers across the world. Figure A2-1 contains a visual representation of the differences in transacting in centralised versus non-centralised environments.

Centralised digital currencies, such as e-money, require the participation of an array of partners and service providers to maintain functionality. These members include, but are not limited to, the primary issuer of the funds, hardware and software providers, clearing and settlements service providers and of course the end user. Cryptocurrency programs, however, are not operated by a central body. Instead, certain intermediaries and exchanges promote the use of the currency in order to facilitate transactions and earn an operations fee. One of the most common intermediaries is the 'wallet' provider who helps facilitate the transfer of funds between participants as well as sovereign currencies. The wallet itself stores the cryptographic keys that represent different amounts of a currency.

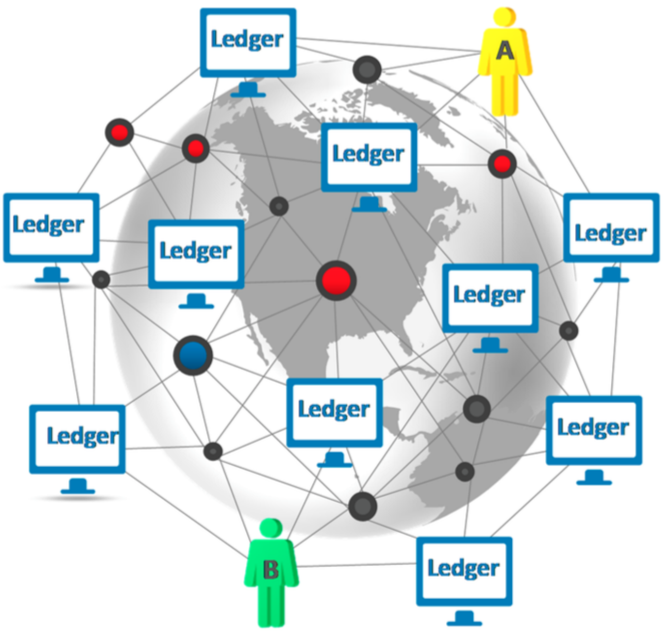
A centralized payment system



Payment from A1 to B1:

- Money is deducted from A1's account in bank A.
- The central bank moves money from bank A's settlement account to B's.
- The central bank maintains central record (ledger) of interbank transactions, by validating transactions and safeguarding against double-spending and counterfeit.
- Bank B adds money to B1's account.
- Banks A and B maintain the ledger of transactions for their clients A1 and B1 respectively.

An illustrative example of distributed ledger system similar to Bitcoin* (Blockchain*)



Payment from A to B:

- Copies of transaction records (ledgers) are kept in multiple computers in the network and visible to anyone.
- The transaction is settled by a multitude of individual nodes (miners), providing computing resources to the network.
- Miners solve a cryptographic puzzle as part of validation process. Miners need to show proof of doing this work to the network (called a "proof-of-work" system), which is costly (computing and energy resources).
- Only the miner who finds the solution faster than any others receives newly minted Bitcoins as reward for their service.
- "Trust" is created by making tampering attempts prohibitively expensive. If a miner wants to record a false transaction, she needs to compete against other miners who are acting honestly (or trying to fake a different transaction).[1]

1/ This mechanism could break down for example if a person or a group takes up 51 percent of the network (mining share), called a "51 percent attack." Some argue that strategic refinement could bring down this threshold to a much lower level (Garrat and Hayes, 2014). Even if a majority is required, the trust machine may break down if some of the miners gain a disproportionally large share of the system (for example, using military or state funds, Swanson, 2015).

Figure A2-1: Taxonomy of Digital Currency Transactions

Source: (He et al., 2016) (IMF.org)

A2.1.3 Types of Distributed Ledgers

There are three major types of distributed ledgers, each of which have their own benefits and drawbacks (Buterin, 2015).

Public ledgers maintain non-centralised ledgers accessible to all those with internet access. This system does not limit who is able to submit new transactions, view old transactions, and participate in the settlement process, including the validation of ledgers and verification of account balances. Participations are largely identified by aliases and are awarded currency for participating in the verification process. It is this compensation that has resulted in the formation of Bitcoin mines; large servers who maintain a copy of the distributed ledger and settle/verify transactions in order to maintain the integrity of the ledger. Bitcoin, Litecoin, Ethereum, as well as all other cryptocurrencies, fall into this category.

Private ledgers require authorization from a designated body in order to participate. They are used to maintain accounts within a single company or entity. As computers can be assigned to the various roles there is no need to compensate participants for maintaining the system.

Hybrid ledgers are typically available to the public but maintained by a pre-determined list of individuals or companies. These participants are usually formally affiliated with the currency, from an operational standpoint, or are end-point users (customers)

The amount and type of information that is contained within the ledger varies across providers. In the majority of cases, only a minimal amount of information is stored, including the transaction amount and non-identifying party indicators (Bitcoin, Litecoin etc.). Few ledgers maintain detailed information including unique payer and payee identifiers and account balances.

A2.2 Key Cryptocurrencies

Currently, some of the key competitors to Bitcoin include Dash, Ethereum, Litecoin, Peercoin, Nxt, and Ripple. Figure 2-10 displays the total market capitalisation of Bitcoin as well as the largest altcoins. Currently, Bitcoin is maintaining its dominance over the market followed by Ethereum and Ripple (XRP). Below we present a brief description of each of the aforementioned altcoins as well as the innovations they have introduced.

Dash began its life as DarkCoin in 2014 it was later renamed to Dash in 2015 due to the potential for its name to be associated with illegal activities. Dash distinguishes itself by allowing for greater anonymity during transactions. It presents users with the option to use the

Darksend method which allows for the complete anonymisation of transactions. It does so by ‘mixing’ the addresses senders with the addresses of the recipients (Duffield & Diaz, 2015).

The Ethereum platform, and its Ether currency, was first developed in 2013 by Buterin (2013). As the first Turing complete cryptocurrency it allows users to create smart contracts with custom parameters. Unlike Bitcoin which generated blocks every 10 minutes, Ethereum generates new blocks every 15 seconds.

Litecoin was originally announced in 2011 by Charles Lee. In 2017, Litecoin gained significantly in popularity due to its technological innovations which allows for the processing of payments in fractions of a second.

Peercoin was first presented in a whitepaper by King and Nadal (2012). It was the first cryptocurrency to use a combination of proof-of-work and proof-of stake mining. These concepts pertain to the method in which voting power is allocated across users. Proof-of-stake allocations voting power based on the value of collateral that miners present, which is usually the number of coins in their position. Proof-of-work allocates voting power based on each miner’s computing power.

Nxt was launched in 2013 by an unknown developer. In this system, users are used alongside miners to verify transactions. Unlike other cryptocurrencies, Nxt does not generate new currency blocks over time. Rather, all coins were allocated to the original 73 investors. As a result, miners and other users who assist in transactions are awarded fees for their efforts as opposed to coins.

Ripple was originally developed in 2012 and was originally intended to facilitate with international transfers quickly and at a low price. In recent years Ripple was modified and now no longer operates on a distributed basis, opting instead for centralised servers to verify transactions.